Dynamic properties of the New-Neoclassical Synthesis model of business cycle

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Abstract

Linear and Hodrick-Prescott detrending methods do not provide a good approximation of the business cycle when output contains a unit root. I use the multivariate Beveridge-Nelson decomposition to document the main patterns of US postwar business cycle when output and some other variables are assumed to be integrated I(1) processes. I show that the business cycle identified in this way displays some important differences with those obtained from the preceding methods. I then evaluate the ability of various dynamic general equilibrium (DGE) models to replicate the main aspects of this business cycle. Among competing models, I find that the best specification involves an economy hit simultaneously by both technological and monetary shocks, in a context of price stickiness and limited (but not sufficient) accommodation by the monetary authorities. Hence, the data favor the model advocated by the New-Neoclassical Synthesis rather than its purely classical (RBC type) or purely Keynesian counterparts.

Keywords: Business cycles, Price rigidities, Beveridge-Nelson decomposition

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1 Introduction

In this paper, I study the extent to which several dynamic stochastic general equilibrium (DSGE) models can reproduce the main features of US postwar business cycle, when the implicit de…nition which is used to characterized economic ‡uctuations is the one proposed by Beveridge and Nelson (1981). I use Beveridge and Nelson's trend-cycle decomposition for two reasons, which are in many respect complementary: First, since the seminal work by Nelson and Plosser (1982), it is widely acknowledged that several macroeconomic variables contain a unit root. It is therefore important to use a …lter which can simultaneously handle a correct treatment of this nonstationarity and to provide a meaningful decomposition between the secular and cyclical components of the data. Second, most detrending procedures commonly used in the real business cycle literature are not really appropriate for evaluating theoretical models whose endogenous variables contain stochastic trends. Considering alternative procedures is then important, at least as a robustness check, before taking strict position in favor or against any speci…c model.

In particular, several authors have criticized the systematic resort to the Hodrick-Prescott …lter as a single method of trend elimination when evaluating the performance of DSGE models[1]. Parts of these critics are theoretical, and rely on the facts that the HP …lter implies a decomposition which is generally inconsistent with the underlying speci…cation of the trend in these models. As a result, its application leads to a violation of most of the moment restrictions implied by these models (Singleton, 1988). On the other hand, several studies have warned against the practical use of the HP …lter by emphasizing that its application to …rst-order integrated series generates strong distortions in the estimated business cycle dynamics[2]. Hence, any attempt to evaluate theoretical models on the basis of these distorted moments would be in fact poorly informative.

By contrast, much of these criticisms can be avoided by using the Beveridge-Nelson decomposition. Notably, one of the key argument in favor of this procedure is that it can viewed as the optimal one-sided estimator of the trend component in a speci…c unobserved component framework (Watson, 1986), and whose structure is veri…ed by most DSGE models (Dufourt, 1999). It avoids therefore much of Singleton's (1988) criticism. Furthermore, the BN de…nition has received great attention in the empirical literature on economic ‡uctuations, notably because the resulting trend-cycle decomposition has a

[1] For a critics against the alternative procedure of mechanically removing linear trends, see Nelson and Kang (1981)

[2] See King and Rebelo (1993), Harvey and Jaeger (1993), Cogley and Nason (1995), Guay and St-Amant (1997), and Dufourt (1999) for a review.

clear economic interpretation. Under the BN decomposition, the cyclical component of a series is defined as the difference between the current value of the variable and the value it is expected to have in the indefinite future (abstracting from its unconditional growth). Ignoring this mean growth, the cyclical component is thus nothing more than the forecastable momentum in the series at each point in time. When applied to production, it can be given a traditional interpretation of an output gap, where potential output is the anticipated long-run level of output, while the cyclical component is simply the gap from that level. This implicit definition of the business cycle is often considered as of primary interest by macroeconomists and economic leaders, who design most economic policies by considering such type of discrepancies between the current level of a variable and a target, which is often defined in relation to its equilibrium (long-run) level.

Because of its ingenuity and its widespread use in the empirical literature, it sounds quite surprising that the BN trend-cycle decomposition has not received as much interest for the evaluation of theoretical models of the business cycle. Since the pioneering work of Rotemberg and Woodford (1996), there is however a strong suspicion that standard DSGE models could fail at accounting for the behavior of US business cycle when it is defined in that way. For example, Rotemberg and Woodford show that the canonical real business cycle (RBC) model with permanent technology shocks is unable to account for the size and the correlations between the forecastable movements of consumption, output and hours worked. Similarly, Rotemberg (1996) shows that a simple flexible price model have difficulties in accounting for the negative correlation between the predictable components of prices and hours worked. These findings are clearly problematic since, in principle, a model of US economy which is correctly specified should be consistent with any definition of the business cycle. Results from these studies suggest instead that several business cycle models could fail along this dimension, even for variables for which they were argued to do well, especially when considered with other detrending procedures such as with the HP filter.

One of the main limitations of Rotemberg and Woodford's work, however, is that it provides an evaluation of the canonical model when it is submitted to only one kind of shock (specifically, a shock to the level of technology). Hence, the inability of this model to account for the business cycle does not necessarily imply that its underlying structure is wrong, but can simply be due to the fact that many other shocks (and, especially, transitory ones) are left aside the analysis. Similarly, while Rotemberg's (1996) model includes technology and monetary disturbances, no capital accumulation is allowed in his economy. As a result, contemporaneous technology shocks generate an immediate response of output, but no future predictable movements. In the end, the dynamics of the forecastable movements is now entirely determined by monetary disturbances. Moreover, no quantitative evaluation in the spirit of the RBC literature can be conducted in this simplified framework.

Building on these considerations, I proposed in Dufourt (1999) a general method to evaluate dynamic rational expectation models with the BN decomposition between fluctuations and trend. Among other things, this method allows a very simple calculation of the asymptotic autocovariance function for the BN cyclical components of the variables, even for models that are submitted to several sources of exogenous disturbances. Hence, it can be used to evaluate the ability of various DSGE models to match the cyclical properties of the data, on the basis of an informal comparison between the main second-order moments implied by the models and their empirical counterparts.

Here, I perform these evaluations for three popular, and competing, models of the business cycle. Specifically, I study a simple DSGE model with capital accumulation and, possibly, nominal rigidities resulting from convex adjustment costs of prices. This model is shown to handle the purely Real Business Cycle (RBC) model studied in Rotemberg and Woodford (1996) and Dufourt (1999), a simple New Classical Economy (NCE) flexible price model with technology and monetary disturbances, and a New Neoclassical Synthesis (NNS) model with both kind of shocks and sticky prices (this terminology follows roughly Goodfriend and King, 1997). I build a set of "stylized facts" for the Beveridge-Nelson cyclical components of most real and nominal variables, and I study the implications of these models regarding this new set of empirical facts.

Overall, numerical evaluations show that the two flexible price models fail significantly over most features of US business cycle when it is defined according to the BN decomposition. I show that these failures apply even for variables which were argued to be correctly described when considered through the window of the HP filter. Furthermore, I argue that there is a sense in which these failures can be considered as structural -inherent to the models' specification, and independent of the relative variance in the exogenous disturbances. By contrast, the NNS model succeeds over practically all the dimensions for which the flexible price models suffered salient failures. These successes are both qualitative (the cross-correlations have the correct sign) and quantitative (the relative magnitudes are closely reproduced). Hence, the data favor strongly the general sticky-price framework advocated by the New Neoclassical Synthesis. I show that the main explanation for these successes lies in the dominant influence the NNS model gives to monetary shocks in the overall predictability of the endogenous variables. Hence, if this model is correct, I argue that effective economic fluctuations are probably mostly driven by monetary disturbances.

The remainder of the paper is organized as follows: In section 2, I detail my empirical strategy for estimating the BN cyclical components of a set of reference macroeconomic variables, which essentially makes use of a multivariate generalization of Beveridge and Nelson proposed by Evans and Reichlin (1994). This allows me to compute the main "stylized facts" along which the theoretical models will be evaluated. Section 3 builds the models, which are in many respect similar to those commonly studied in the business cycle literature. Section 4 displays the results and the main explanations for the performance of each models. Finally, Section 5 documents shortly the characteristics of economic ‡uctuations implied by the NNS model.

2 Empirical analysis

In this empirical analysis, I address two kind of issues. First, I wonder whether a stochastic growth model with money generates series that have stochastic properties similar to the data[3]. Part of this question was already answered by King, Plosser, Stock and Watson (1991) in a context of a purely real model, but I extend this analysis to a fully speci…ed model that includes nominal variables. Second, I show how to compute consistently the Beveridge-Nelson cyclical component of the variables, using a modi…ed procedure of the multivariate generalization of Beveridge and Nelson (1981) proposed by Evans and Reichlin (1994). I then compute the relevant second order moments for these variables, and I document the main characteristics of the business cycle identi…ed in this way.

2.1 The data

My data set consists of quarterly observations from the DRI economic database (formerly Citibase) for the sample 59:1 to 93:4[4]. My measure of private output Y_t is the di¤erence between real GDP and government sector value-added output. The measure of consumption C_t includes personal consumption expenditures in nondurable goods and services. Hours H_t are total hours

[3] Throughout this study, I use the term 'stochastic properties' to refer to the presence of (possibly common) stochastic or deterministic trends in the series.

[4] The sample ends in 93:4 because I use the series on hours worked that is based on the household survey, and which ends up in 93.4. I use this series instead of the series based on the establishment survey, because I wasn't able to reject the presence of a unit root in the latter series, which would have created an inconsistency with the theoretical model of section 3. I use linearly detrended- instead of per-capita hours, because the latter series still has a slight deterministic upward trend.

worked in the private sector, estimated according to the household survey. Money M_t is M1, the nominal interest rate R_t is the federal fund rate, and the price index P_t is the corresponding output deflator. In addition, I define the inflation rate π_t as P_t/P_{t-1}, the money growth rate g_t as M_t/M_{t-1}, and the level of productivity Q_t as Y_t/H_t. All these variables are logged, except the inflation rate, the money growth rate, and the nominal interest rate, the latter being converted to a quarterly basis to be consistent with my measures of money growth and inflation. A precise definition of the data with their Citibase mnemonic is provided in appendix A.

2.2 Stochastic properties of the data

Before computing the BN second order moments of the series, one has to make sure that the stochastic properties of the model-generated data are consistent with those of US data. This is an important stage, since any comparison between the BN cyclical components of the model and the data would be spurious if the series had not the same stochastic properties. In addition, this preliminary stage is a fundamental step for a correct specification in the VAR-based methodology discussed later. My general strategy to address this issue is as follow: throughout the analysis, I will consider as the null hypothesis the assertion that the model is correct, and I will use this null hypothesis as the basis for a test applied to the data. For example, if the model implies that a variable (or, eventually, a linear combination of several variables) is integrated of order one, I will test the null hypothesis that this series is indeed I(1) in US data. If this null cannot be rejected at conventional significance level, then I will conclude that the model does indeed generate a series for this variable that has stochastic properties consistent with that of the data. King, Plosser, Stock and Watson (1991, henceforth KPSW) pursued a similar strategy using the canonical RBC model with a unit root in the level of technology. As noted before, my analysis extends to several other variables (listed above), since the theoretical model in section 3 also implies testable restrictions on the stochastic properties of these variables as well.

I first consider the behavior of the most important real variables (see Panel A of Table 1). When the Solow residual is modeled as a random walk, KPSW showed that the theoretical model implies that output and consumption should be integrated of order one, but that their ratio should be stationary. In other terms, c and y are cointegrated with cointegrating vector (1,-1). Results in Table 1 show that, although I use a data set slightly different from KPSW, this hypothesis is still validated for postwar US data. Using both Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests,

Table 1-Unit root tests

A. Real variables

Variable	t-stat (ADF)	t-stat (PP)	Critical (5% - 1%)
y [(a)]	-2.24	-2.23	(-3.44) - (-4.02)
Δy [(b)]	-5.09	-9.62	(-2.88) - (-3.48)
c [(a)]	-1.28	-1.07	(-3.44) - (-4.02)
Δc [(b)]	-4.50	-8.86	(-2.88) - (-3.48)
$c - y$ [(b)]	-2.82	-2.93	(-2.88) - (-3.48)
h [(a)]	-4.67	-3.51	(-3.44) - (-4.02)
q [(a)]	-1.66	-2.04	(-3.44) - (-4.02)
Δq [(b)]	-5.41	-12.71	(-2.88) - (-3.48)

B. Nominal variables

Variable	t-stat (ADF)	t-stat (PP)	Critical (5% - 1%)
p [(a)]	-2.37	-2.36	(-3.44) - (-4.02)
Δp [(b)]	-1.97	-3.29	(-2.88) - (-3.48)
m [(a)]	-1.99	-2.40	(-3.44) - (-4.02)
Δm [(b)]	-2.91	-5.53	(-2.88) - (-3.48)
R [(b)]	-2.21	-2.36	(-2.88) - (-3.48)

Note: Specification (a) includes a time trend and a constant in the null. Specification (b) only includes a constant.

Table 1 shows that c and y can be considered as I(1) processes, but that the ratio c-y is best modeled as a stationary one[5]. Hence, the model appears consistent with the data along this dimension. On the other hand, the theoretical model implies that hours worked are trend-stationary. Testing this restriction, Table 1 shows that the presence of a unit root in hours worked is strongly rejected for the ADF test (the t-statistic is well above the 1% critical value), and rejected at the 5% level with the PP test. Again, the null hypothesis implied by the model seems validated with postwar US data. Finally, Table 1 shows that productivity is best modeled as an I(1) process, a finding that is again consistent with the theoretical model in section 3.

Now I turn to the stochastic properties of the nominal variables (Panel B of Table 1). As will be seen in the next section, the theoretical model implies

[5] Although the t-statistic lies between the 5-10% interval for the ADF test, it is above the 5% value for the PP test.

that the price index and the money level should be integrated, but that in‡ation and the money growth rate should be stationary. In other terms, prices and money are predicted to be I(1) series. Table 2 shows that this prediction is easily validated using both tests for the data on M1: while the presence of a unit root cannot be rejected in the level of money, it is clearly rejected for its rate of growth (the t-statistic is above the 5% critical value for the ADF test and well above the 1% value for the PP test). There is a small ambiguity, however, considering the price level: both tests indicate that the presence of a least one unit root in this series cannot be rejected, which is consistent with the theoretical model. But the ADF test does not either reject the presence of a unit root in the in‡ation rate (the t-statistic is only -1.97 compared to a 5% critical value of -2.88), whereas the model predicts this rate should be stationary. Based on the PP test, however, stationarity of the in‡ation rate is validated at the 5% level. Given this contradictory evidence, I conclude that the model-implied null hypothesis that prices are only I(1) cannot be rejected with much con…dence, and hence that the model is consistent with the data for this series as well.

Consider now the results for the interest rate: the model in section 3 predicts that this rate should be stationary. According to Table 1, however, non-stationarity for the federal fund rate cannot be rejected. This result is similar to several studies that found non-stationarity for the interest rate (see Fuhrer and Moore (1995), Galí, 1999). However, as noted by Fuhrer and Moore and Clarida, Galí and Gertler (1998), among others, this non-rejection of a unit root in nominal interest rate does not have a very meaningful economic interpretation: It may instead be due to the low power of unit root tests when the sample is small and the autoregressive coe¢cient is high, an hypothesis that is likely to occur given the recognized desire by the monetary authorities to smooth variations in the federal fund rate. Note that it is possible, given the former results on in‡ation, to run an alternative test for stationarity in the nominal interest rate. Consider for that matter the de…nition of the ex-post real rate: $r_t = R_t - \Delta p_{t+1}$. If in‡ation and the real rate can be considered as I(0) processes, then R_t must be I(0) as well. Conducting this experiment, I obtained the same ambiguity for the real interest rate as for the in‡ation rate. The t-statistic for the ADF test is slightly below the 10% critical level, implying a non-rejection of the null of a unit root, while for the PP test it is above the 5% level (-3.07 compared to a critical value of -2.88). Hence, if one is con…dent that in‡ation is a stationary process, one may be con…dent that the nominal interest rate is stationary as well. Together with the former discussion, this led me to think that stationarity for the nominal rate is probably the best specification[6].

Overall, results in this section suggest that simple DGE models with money and a unit root in the level of technology generate series whose stochastic properties are consistent with those of US. data. According to me, this finding reinforces the need to consider such a specification compared with its trend-stationary alternative. In addition, given the preceding discussion on the perverse effects of HP filtering I(1) series, it seems important, at least as a robustness check, to evaluate the success of these various DGE models with other filters that are more consistent with the specification of the underlying trend, as recommended by Koopmans(1965) and Singleton (1988). As I argued, the BN decomposition is such a filter.

2.3 Computing the Beveridge-Nelson cyclical components

Now that I have verified the consistency between the stochastic properties of the model-generated series and US. data, it is possible to compare their BN cyclical components. To compute these components for US data, I used the following strategy: Recall that Beveridge and Nelson (1981) defined the cyclical component of a series y_t by

$$y_t^{cyc} = \lim_{k \to \infty} \{y_t - E(y_{t+k} \mid ..., y_{t-1}, y_t) - k\mu\} \quad (1)$$

where μ is the long run mean of Δy. Hence, the cyclical component of y at t depends on the date-t forecast of this variable for the infinite future. As is apparent from (1), Beveridge and Nelson based this forecast on the past values of the variable only. However, as noted by Evans and Reichlin (1994) and Rotemberg and Woodford (1996), there is no *a priori* reason to do so. Indeed, many other variables may potentially help to forecast y at t, and these variables should be taken into account when defining the cyclical component of y. A natural generalization of Beveridge and Nelson (1981) is then to rewrite the cyclical component as

$$\hat{y}_t^{cyc} = \lim_{k \to \infty} \{y_t - E(y_{t+k} \mid \Omega_t) - k\mu\} \quad (2)$$

[6] Notice that this restriction is not very crucial, since it is perfectly possible to build a DGE model in which inflation and the interest rate are I(1). The choice between the two specifications then mostly depends on the preference of the modeler. As for Fuhrer and Moore (1995), Clarida et al. (1998), and almost all the studies on the topic reviewed in Taylor (1999), my own view is that, regarding the way monetary policy is conducted in the US, specifying a unit root in the nominal interest rate is probably undesirable.

where Ω_t is the information set available at date t. In theory, every variable that belongs to Ω_t should be used to forecast y. In practice, Evans and Reichlin, Rotemberg and Woodford, and Rotemberg (1996), first estimated a VAR including most relevant variables, and then computed the forecast of these variables using the estimated representation of the VAR. According to definition (2), the implicit assumption that underlies this procedure is that each included variable in the VAR belongs to the information set Ω_t.

A problem that may arise with this methodology is that if a variable is wrongly included in Ω_t, then the VAR may be misspecified and the computed forecasts may become irrelevant. This could induce in turn a wrong characterization of the cyclical component of the variables. This problem is likely to occur if one wishes to study the cyclical component of a large number of variables, as is the case for the present study. To avoid this difficulty, I used a slightly different strategy which is as follows: As in Rotemberg (1996) and Rotemberg and Woodford (1996), I first started by estimating a VAR under the form

$$Z_t = AZ_{t-1} + \epsilon_t \tag{3}$$

where Z_t is a vector containing all the variables of interest and p lags of them. Then, equation by equation, I ran an F-test for each included variable. If these tests implied that one or several variables do not statistically contribute to explain the endogenous variable at the 5% level, then I dropped the variable with the least significant coefficient and restarted the procedure until each remaining variable was significant. In the end, for every variable under consideration, I have computed an information set for which I can accept the hypothesis that each included variable does indeed belong to the information set and contributes to forecast the endogenous variable. The new representation for this modified VAR is

$$Z_t = A'Z_{t-1} + \epsilon'_t \tag{4}$$

where A' is a matrix with zero entry for the excluded variables, the other parameters being estimated by simple OLS regression. I believe this new procedure helps to define a more accurate Beveridge-Nelson cyclical component than the one based on the unrestricted VAR, especially when a large number of variables are included.

Given now an estimate of the coefficient matrix A' and the corresponding residuals, it is straightforward to compute the BN cyclical component of the variables and their second order moments. Specifically, define the two matrices B_1^k and B_2^k as

$$B_1^k = \left[A' + A'^2 + \ldots + A'^k\right] \tag{5}$$

and

$$B_2^k = A'^k - I \tag{6}$$

For a variable z that enters the VAR in first difference (and after demeaning), it is straightforward to show that

$$\underset{t}{E}\,(z_{t+k}) - z_t = e_z' B_1^k Z_t \tag{7}$$

where e_z is a column vector with one in the z^{th} raw and zero elsewhere. Similarly, for a stationary variable (linearly detrended), one has

$$\underset{t}{E}\,(z_{t+k}) - z_t = e_z' B_2^k Z_t \tag{8}$$

Hence, the BN cyclical component of z is given by

$$z_t^{cyc} = \lim_{k \to \infty} \left\{ z_t - \underset{t}{E}\, z_{t+k} \right\} = -e_z' B_j^{\infty} Z_t \tag{9}$$

for $j = 1; 2$ according to whether the variable is difference or trend-stationary. In practice, taking a large k (such as 100) is largely sufficient to ensure convergence[7]. Denote now an estimate of the variance-covariance matrix of Z_t (computed from the estimated residuals using standard techniques) by $\widehat{\Sigma}$. Then it follows from definition (9) that an estimate of the variance of the BN cyclical component of z is given by

$$\widehat{Var}\,(z_t^{cyc}) = e_z' B_j^k \widehat{\Sigma} B_j^{k\prime} e_z \tag{10}$$

for k large enough. Similarly, the covariance in the cyclical component of two variables x and z is given by

$$\widehat{Cov}\,(x_t^{cyc}; z_t^{cyc}) = e_x' B_i^k \widehat{\Sigma} B_j^{k\prime} e_z \tag{11}$$

for k large enough, and $(i; j) \in (1; 2)$ according to whether $(x; z)$ are difference or trend-stationary. Hence, applying formulae such as (10) and (11) allows a very simple calculation of the main second order moments of the BN cyclical components of any variable included in the VAR.

[7] Note that, for series that do not contain a unit root, standard stability conditions of VAR analysis implies that $\lim_{k \to \infty} B_2^k = -I$, and hence that the BN procedure does not alter linearly detrended variables. This is perfectly consistent with the definition of Beveridge and Nelson since for such series the long run forecast is simply the linear trend. I introduce the notation (6) just to facilitate the exposition of calculations.

2.4 Empirical results

I applied this procedure for a vector Z_t specified so as to compute the cyclical component of all the series studied in the previous section. More specifically, Z_t is defined as

$$Z_t = \begin{bmatrix} \Delta y_t \\ c_t - y_t \\ h_t \\ \Delta p_t \\ R_t \\ \Delta m_t \\ \Delta y_{t-1} \\ \cdots \end{bmatrix}$$

with two lags of each variable included. The number of lag has been chosen so as to drop any significant serial correlation in the estimated residuals. Note that this specification is consistent with the unit root tests conducted above, by notably imposing cointegration between c and y and allowing for one unit root in y, p, and M[8,9]. Note also that this limited set of variables is sufficient to compute the empirical BN cyclical component of every variable under consideration in the previous section, since the cyclical component of the missing series can in fact be uncovered as simple linear combinations of the others. For example, the cyclical component of productivity can easily be uncovered from those of output and hours worked. Similarly, the cyclical component of consumption may be computed as a direct combination of those of output and the ratio $c - y$.

Estimating the VAR as in (4) gave results displayed in Table 2. Some of these results are worth stressing:

First, there is a significant forecastable component in output growth (the R^2 is about 0.3). This implies that an important part of output variations are

[8] Note that, as noted by Evans and Reichlin (1994), imposing an error correction term for c and y in the VAR specification should not be necessary for the computation of the BN cyclical component of the variables, because in principle this EC term does not add supplementary information for the long run forecast of these variables (at least, asymptotically). I included this ratio instead of c alone, because this ratio has been shown by several studies to be an excellent forecaster of output growth, as the basic permanent income theory predicts. See, for example, Campbell (1987) for a most well-known reference on that point.

[9] The same argument explains why I didn't try to impose a cointegration relationship between real balance $m - p$ and real income y. Although this cointegration relationship has been found in several studies, I wasn't able to establish it with my data set. Results in Evans and Reichlin (1994) suggest that, in practice, this is of no importance.

Table 2—Regression results

Explanatory variables	Δy	$(c-y)$	h	Δp	R	Δm
Constant	-0.218 (-2.27)	0.240 (2.68)	-0.003 (-2.98)	0.099 (2.57)	-0.070 (-1.84)	0.226 (2.32)
Δy_{-1}	0.866 (4.50)	-0.609 (-3.38)	0.219 (3.20)		0.043 (1.96)	
Δy_{-2}	0.078 (0.99)	-0.017 (-0.23)	0.100 (1.61)		0.040 (2.10)	
$(c-y)_{-1}$	0.934 (4.48)	0.283 (1.45)				
$(c-y)_{-2}$	-0.789 (-3.61)	0.621 (3.04)				
h_{-1}			0.936 (9.95)		0.031 (1.11)	
h_{-2}			-0.020 (-0.21)		0.003 (0.10)	
Δp_{-1}				0.607 (7.36)	0.003 (0.04)	
Δp_{-2}				0.266 (3.24)	0.132 (1.88)	
R_{-1}				0.405 (4.17)	1.024 (11.00)	-1.716 (-6.93)
R_{-2}				-0.375 (-3.90)	-0.146 (-1.58)	1.777 (7.25)
Δm_{-1}	0.067 (0.61)	-0.056 (-0.54)			0.114 (4.61)	0.391 (5.22)
Δm_{-2}	0.200 (1.89)	-0.210 (-2.08)			-0.058 (-2.26)	0.326 (4.17)
R^2 (adj)	0.30	0.86	0.86	0.82	0.93	0.54

Note: t-statistics are given in parentheses under coefficient estimates.

due to 'business cycle' fluctuations (as I defined them), instead of variations in the underlying trend. Furthermore, only a fraction of this forecastable component is due to the autocorrelation of output growth, and many other variables help to forecast that component as well. This implies that the cyclical part of output is probably much better defined with several variables than using only the past values of the series, as the basic Beveridge-Nelson decomposition does. This justifies in turn the multivariate approach I retained.

Next, among the variables that help to forecast output growth, one is real (the ratio $c - y$, as expected), and one is nominal (money growth). This suggests that the purely real interpretation of the business cycles is probably wrong, and that an important part of output fluctuations may be due to monetary factors. Note that when money and the interest rate are included separately in the regression, both help to predict output growth.

However, both series seem to gather the same kind of information, since the extra-explanatory power of the interest rate vanishes when money is already included in the equation. On the other hand, when included separately, money seems to provide more informations on output growth than the fund rate does.

Another implication of that …rst regression is that the series on hours worked does not appear to be such a good forecaster of output growth as was suggested in former studies. Indeed, when other variables are included, this series losses most of its explanatory power.

Note …nally that all the signs associated with the regression coe¢cients are consistent with what is expected from economic theory. For example, an high saving ratio (a low c ¡ y) is associated with a low future output growth, as is predicted by the permanent income theory. Similarly, an high money growth rate predicts a strong future output growth, as is consistent with monetary theory.

Considering now the other regressions in Table 2, one notable feature that emerges is the absence of a recognizable Phillips curve in these regressions. Indeed, the series on hours worked is only explained by its own lags and past output growth, and in‡ation is not explained by hours worked either. On the other hand, in‡ation is well explained by the fund rate. More precisely, in‡ation is high when the fund rate was high one quarter ago. This …nding may re‡ect the (partially unsuccessful) preemptive …ght by the monetary authorities against in‡ation.

Finally, the regression concerning the nominal interest rate gave pretty much the same results as the empirical studies which tried to account for the behavior of US monetary authorities: Interest rates are raised following an above-than-average output growth or an high in‡ation rate. Furthermore, interest rates are strongly linked to their own lags. As I argued, this probably re‡ects the desire of the Federal Reserve to smooth interest rates variations. Another striking feature is that the state of the labor market seems to have an in‡uence on the way monetary policy is conducted, since the series on hours worked signi…cantly explains the behavior of the fund rate. Although this …nding may not be a surprise for an economic observer, it stands a little bit in contrast with the academic literature that (almost) never takes into account such an e¤ect.

Now I turn to the results for the estimated BN cyclical components. Most of these results are displayed in …gures 1-3 and Table 3. Figures 1 and 2 plot the estimated cyclical components of output with the troughs of recessions as determined by the NBER. From these graphs, it is clearly apparent that the recessions of output identi…ed with the multivariate approach are much more strongly correlated with NBER troughs than those obtained from the

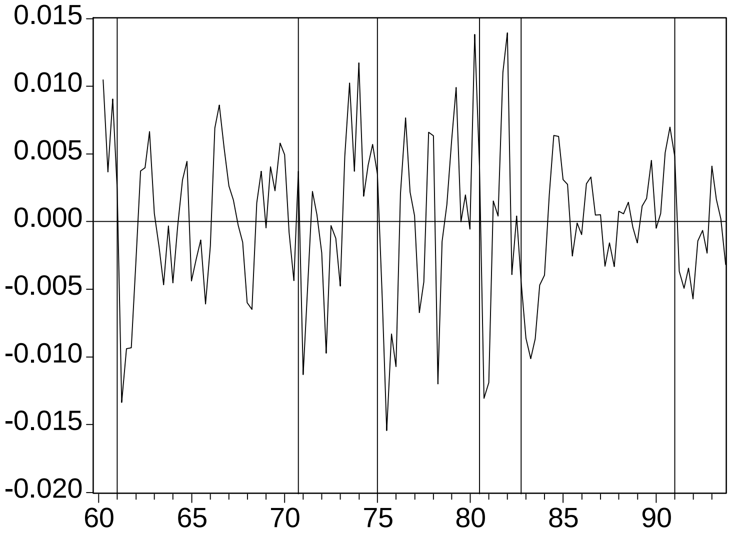

Figure 1: cyclical component of output (univariate BN, 5 lags inluded) and NBER troughs.

original Beveridge and Nelson univariate estimates.

Next, figure 3 plots the BN versus HP cyclical parts of output. As may be seen, both filters extract roughly the same 'business cycle' component of output, although the interpretation given to this business cycle is fundamentally different[10]. This figure confirms however, from an intuitive point of view, the relevancy of the business cycle extracted using the multivariate BN decomposition.

Table 3 displays the relative standard deviations and the contemporaneous cross-correlation of each variable with output, after filtering by the BN filter. For the sake of comparison, the same moments are reported when these variables were filtered using the HP filter. Results with the HP filter have been extensively documented and are now very familiar (see, e.g., Cooley and Prescott (1995), and Cooley and Hansen, 1995): consumption

[10] It should be noted that the similarity in the BN and HP cyclical components of output is for a large part a pure coincidence, and is not due to a general property of these filters. For other series, such as the price level, the estimated cyclical components were extremely different. The fact that different filters extract different cyclical components should not be considered as abnormal, since each filter is associated with an implicit definition of the business cycle which is different from the other. As I argued, a problem for the HP filter is that, when there is a unit root in the series under consideration, this implicit definition of the business cycle is unclear.

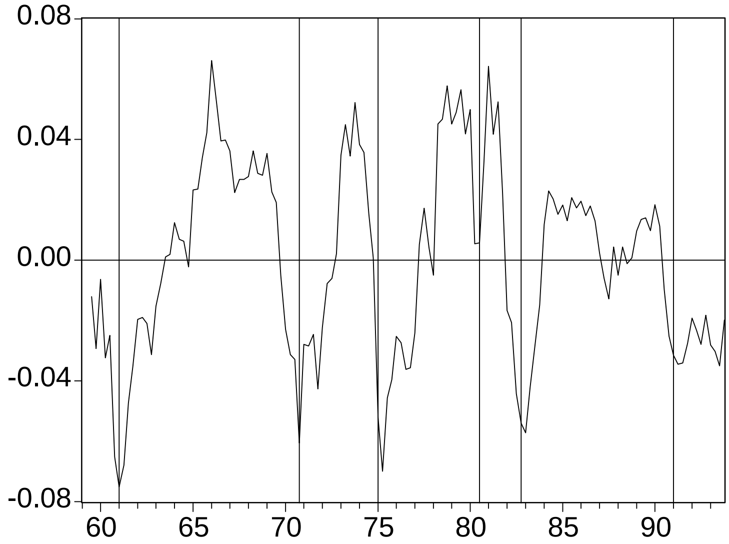

Figure 2: Cyclical component of output (multivariate BN) and NBER troughs.

and productivity are less volatile than output and highly procyclical. Hours worked are slightly less volatile than output and are also procyclical. The nominal interest rate and the money level are slightly procyclical, while the correlation between HP …ltered prices and output is strongly negative, prices being less volatile than output (see also Cooley and Ohanian, 1991). Finally, in‡ation is weakly positively correlated with output, while the money growth rate is weakly negatively correlated with it, both series being less volatile than output.

Consider now the same 'stylized facts' obtained with the BN …lter: As for the HP …lter, Table 3 indicates that the cyclical components of consumption and productivity are less volatile than output and strongly positively correlated with it. However, hours worked are now about half as volatile as output, and are much less procyclical. The most notable results stand however for the nominal variables: Indeed, the price level's cyclical component is now much more volatile than those of output (the ratio is about 1.86), while the opposite is true with the HP …lter. Similarly, the cyclical component of money is now twice as volatile as output, while it is of equal volatility with the HP …lter. If the instantaneous price-output correlation remains of the same sign, the money level-output correlation now turns negative. On the other hand, output becomes positively correlated with money growth, while

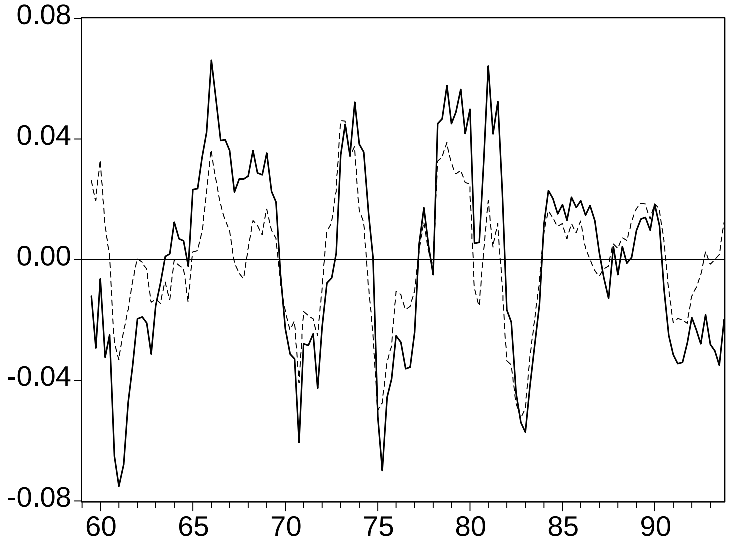

Figure 3: BN vs HP cyclical components of output (straigth line: BN, dashed line: HP, adj.)

the opposite was true when these series were …ltered with the HP …lter.

Hence, it is clearly apparent that the overall pattern of US business cycle is very di¤erent according to whether one uses the HP or the BN …lter to decompose a series into a trend and a cyclical component, a point also documented in Canova (1998). It should be stressed however that one must remain extremely careful when interpreting the 'business cycle facts' identi…ed with the Beveridge and Nelson procedure. For example, the …nding of a negative correlation between the money level and output cyclical components does not in any way require that these series must move in opposite direction in response to at least one shock. It only stresses that, in general, output is expected to decline (in the long-run) when money is expected to increase. This is perfectly consistent with a contemporaneous response of both series to a shock in the same direction, as long as money is still expected to increase after that shock while output is expected to return its original level (as, for example, long-run monetary neutrality would require). Hence, for the same behavior of money and output, the HP …lter will naturally extract business cycle components that are positively correlated, while the opposite will result from …ltering this series with the BN procedure. As I explained above, this is essentially the result of a di¤erence in the de…nition of the business cycle rather than an abnormality of one of these …lters. Still, the theoretical

	Relative std. dev.		Contemporaneous cross-correlation with output	
Variable	BN	HP	BN	HP
y	1	1	1	1
c	0.57	0.42	0.95	0.84
h	0.49	0.68	0.53	0.82
q	0.85	0.58	0.87	0.73
R	0.25	0.19	0.68	0.32
p	1.86	0.49	-0.23	-0.70
¼	0.14	0.16	0.31	0.12
m	2.10	0.96	-0.60	0.30
g	0.22	0.39	0.32	-0.10

Table 3 - Empirical second order moments

models, under the null assumption that they are true, should be consistent with any de…nition of the business cycle. This is another reason for assessing their success with the BN …lter.

Before closing this section, it should be said at the outset that my Beveridge and Nelson based pattern of US business cycle is consistent with …ndings apparent in other studies. For example, Rotemberg and Woodford (1996) reported a positive correlation in the forecastable components of output, consumption, and hours worked, and Rotemberg (1996) found a negative correlation between the forecastable movements in prices and output. All theses results are consistent with those displayed in Table 3. Similarly, Canova (1998) reported a positive correlation in the BN cyclical components of output, consumption, and hours worked. One notable di¤erence, however, is that he found a negative correlation in the cyclical components of output and productivity, while my results suggest that this correlation is strongly positive. This di¤erence is essentially due to the use by Canova of the univariate BN detrending method instead of the multivariate approach retained in this paper. As I argued, and in light of …gures 1-2, I believe that the cyclical components of the data are much better de…ned with the multivariate …lter, and hence that the positive correlation reported here is probably the most robust fact.

3 The model

Since my aim is to identify successes and failures of existing business cycle models along dimensions underlined with a di¤erent …lter than those commonly used, I chose to study a very canonical model that can easily be compared with similar models in the literature which were evaluated using these traditional filters. Hence, my model is a simple monetary model with monopolistic competition on the goods market and (possibly) nominal rigidities resulting from convex adjustment costs of prices. It is strongly based on existing monetary models such as Christiano and Eichenbaum (1992), Hairault and Portier (1993), Yun (1996) or Ireland (1997a) (among many others), although it differs from each of them in some details. The economy is composed of a continuum of infinitely lived households that maximize their expected utility, a continuum of infinitely lived differentiated firms maximizing their expected profit, a representative financial intermediary that collects money from households and lends it to the firms, and the monetary authority.

3.1 Program of the representative household

The representative household takes two kind of decisions: First, it decides how much money S_t it allocates to the bank, knowing that it must finance by cash its consumption purchases P_tC_t. Denoting by M_{t-1} the amount of money accumulated from the preceding period, the corresponding cash-in-advance constraint is

$$M_{t-1} \geq S_t + P_tC_t \tag{12}$$

Second, the representative household chooses its level of consumption C_t and hours worked H_t, taking as given the nominal wage W_t. In addition to its labor income, the household receives at the end of period t its interest-augmented amount of deposits R_tS_t, as well as a fraction Π_t and F_t of all the profits made by the firms and by the representative financial intermediary. It then carries an amount M_t of money to the next period, according to the budget constraint

$$M_t \leq W_tH_t + S_tR_t + \Pi_t + F_t + (M_{t-1} - S_t - P_tC_t) \tag{13}$$

The household's problem at date 0 is then to choose contingency plans for C_t, H_t, S_t and M_t, $t = 0 \ldots \infty$, to maximize

$$\sum_{t=0}^{\infty} \beta^t U(C_t; H_t)$$

with respect to its information set at date t (which contains all variables dated t and earlier) and constraints (12) and (13). β is the discount factor which satisfies $0 < \beta < 1$. I assume that the instantaneous utility function is logarithmic in consumption and leisure

$$U(C_t; H_t) = (1-\gamma)\ln(C_t) + \gamma \ln(1-H_t) \tag{14}$$

with $\gamma \in [0;1]$. The first-order conditions of this program can be written as

$$\frac{\gamma}{1-\gamma}\frac{C_t}{1-H_t} = \frac{1}{R_t}\frac{W_t}{P_t} \tag{15}$$

$$\underset{t}{E}\{P_{t+1}C_{t+1}\} = \beta R_t P_t C_t \tag{16}$$

as well as equations (12) and (13) which are constrained to hold with equality. Equation (15) is the traditional trade-off equation between consumption and leisure, and equation (16) is the no less traditional trade-off equation between current and future marginal utilities of consumption.

3.2 Program of the firms

The economy contains a continuum of firms which produce differentiated goods. These differentiated goods are aggregated into a single composite good that can either be consumed or used to increase the capital stock K_t. Assuming that all goods are imperfect substitutes with a constant elasticity of substitution θ ($\theta > 1$), the corresponding Dixit-Stiglitz (1977) aggregator can be defined as

$$Y_t = \left(\int_0^1 \left(Y_t^i\right)^{\frac{\theta-1}{\theta}} di\right)^{\frac{\theta}{\theta-1}} \tag{17}$$

where Y_t^i is the amount of good produced by firm i. It is well-known that under such an aggregator, the typical demand function addressed to firm i is given by

$$Y_t^i = \left(\frac{P_t^i}{P_t}\right)^{-\theta} Y_t \tag{18}$$

where P_t is the dual price index satisfying

$$P_t = \left(\int_0^1 \left(P_t^i\right)^{1-\theta} di\right)^{\frac{1}{1-\theta}} \tag{19}$$

Taking as given the demand function (18), each firm combines K_{t-1}^i units of capital and H_t^i units of hours worked to produce output according to the production technology[11]

$$Y_t^i = \left(K_{t-1}^i\right)^{\alpha}\left(z_t H_t^i\right)^{1-\alpha} - z_t\phi \tag{20}$$

where z_t is an exogenous labor-augmenting technological progress, and ϕ is a fixed-cost. I assume that this labor-augmenting technological progress follows a logarithmic random walk with drift,

$$\ln z_t = \ln z_{t-1} + \mu + \varepsilon_{z,t} \tag{21}$$

where $\varepsilon_{z,t} \sim N(0, \sigma_z^2)$ is a serially uncorrelated technological shock.

Furthermore, it is assumed that firms own their capital stock and accumulate it according to

$$K_t^i = (1-\delta)K_{t-1}^i + I_t^i \tag{22}$$

where $\delta \in [0, 1]$ is the depreciation rate of capital (common to all firms) and I_t^i is investment. As noted earlier, investment is made with the same final good that is used for consumption. I require that firms finance investment purchases $P_t I_t^i$ on a pre-paid basis by borrowing to the bank the appropriate amount of cash at the nominal interest factor R_t.

In addition, in some variants of the model, firms will have to incur quadratic adjustment costs to modify their nominal price. I assume that the adjustment cost function is measured in terms of the final good and is given by

$$C\left(\frac{P_t^i}{P_{t-1}^i}\right) = \frac{\Phi_P}{2}\left(\frac{P_t^i}{P_{t-1}^i} - \pi\right)^2 Y_t \tag{23}$$

where $\Phi_P > 0$ is a parameter governing the size of the adjustment costs, and π is the steady state rate of inflation. This formulation of nominal price rigidities is similar to those in Rotemberg (1982), and is chosen as a simplification of a more realistic process such as imbricated price contracts[12].

Finally, the problem of firm i is to choose contingency plans for H_t^i, K_t^i, Y_t^i, P_t^i and I_t^i, $t = 0, \ldots, \infty$ to maximize

[11] Note that I use the convention that all variables dated t must be chosen in period t. Since capital in t is decided in t-1, it is dated t-1.

[12] Indeed, I do not argue here that such a process explains empirically the presence of a strong sluggishness in nominal prices. However, it has been shown by Rotemberg (1982) that the dynamics implied by this highly stylized form of price rigidity is similar to those of a much more realistic explanation proposed by Calvo (1983), in which prices contracts are imbricated but firms have constant probability of adjusting their price. Hence, I chose the former specification just as a convenient approximation of this type of price rigidity.

$$\sum_{t=0}^{\infty} \frac{\rho_{t+1}}{\rho_0}\left(P_t Y_t^i - W_t H_t^i - P_t I_t^i R_t - P_t C\left(P_t^i / P_{t-1}^i\right)\right) \tag{24}$$

subject to the demand function (18), the law of motion of capital (22), and the production technology (20).

In (24), ρ_t represents the period 0 value of a claim that provides one unit of period t composite good in all period t contingencies. Hence the ratio $\frac{\rho_{t+1}}{\rho_0}$ can be interpreted as the implicit discount rate of the firms[13]. Although, for simplicity, I do not model an explicit market for this asset, I use its implied non-arbitrage relationship with the nominal return on deposits R_t, which is given by (see Sargent, 1986)

$$\frac{\rho_{t+i}}{\rho_t} = E_t\left\{\frac{1}{R_t \cdots R_{t+i-1}}\right\} \tag{25}$$

After eliminating the Lagrange multipliers, and by appropriate substitutions, the first order conditions of the above program can be written as

$$\left[\left(\frac{P_t^i}{P_t}\right)^{-\theta} - \phi_P\left(\frac{P_t}{P_{t-1}^i}\right)\left(\frac{P_t^i}{P_{t-1}^i} - \pi\right) - \theta\left(1 - \frac{W_t H_t^i}{(1-\alpha)P_t^i Y_t^i}\right)\left(\frac{P_t^i}{P_t}\right)^{-\theta}\right] Y_t$$

$$+ E_t\left\{\frac{\rho_{t+2}}{\rho_{t+1}}\phi_P\left(\frac{P_{t+1}}{P_t^i}\right)\left(\frac{P_{t+1}^i}{P_t^i}\right)\left(\frac{P_{t+1}^i}{P_t^i} - \pi\right) Y_{t+1}\right\} = 0 \tag{26}$$

$$P_t R_t = E_t\left\{\frac{\rho_{t+2}}{\rho_{t+1}}\left[\frac{\alpha}{1-\alpha}\frac{W_{t+1}H_{t+1}^i}{K_t^i} + (1-\delta)P_{t+1}R_{t+1}\right]\right\} \tag{27}$$

Note from these equations that when $\phi_P = 0$, i.e. there are no costs of adjusting prices, (26) and (27) reduce to the more traditional (flexible prices) equations that relate the marginal productivities of labor and capital to their implicit prices, and over which a constant markup $\frac{\theta}{\theta-1}$ is applied (see, for example, Rotemberg and Woodford, 1995).

3.3 The monetary authority

The monetary authority manages the nominal money supply M_t by injecting new cash X_t via lump-sum transfers to the financial intermediaries. Hence,

$$M_t = M_{t-1} + X_t$$

[13] The fact that the first period profit in (24) is actualized reflects the condition that firms profits at period t are only available to consumers at period t + 1.

Early monetary business cycle models have usually represented monetary policy as a purely exogenous process involving the growth rate of money. This stood in sharp contrast with the empirical literature which stresses that a large component of monetary innovations is highly related to the state of the economy. The monetary authority is often viewed as following a policy rule of the type suggested by Taylor (1993), with the federal fund rate reacting to innovations in the past levels of output and inflation. A difficulty when one tries to model such a policy rule (or variants of it, as in Clarida, Galí and Gertler, 1998) is that for the estimated values of the parameters in the policy rule, the theoretical model often turns to become indeterminate and to allow for self fulfilling prophecies equilibria (see Clarida, Galí and Gertler (1998) for a discussion). As this problem applies here, and since I want to avoid many complications resulting from the possibility of multiple equilibria, I follow instead the mixed strategy introduced in Yun (1996), Ireland (1997a), Ambler et al. (1999) and Galí (1999), by specifying the monetary policy rule as one that involves the growth rate of money but partially accommodates technology shocks. Hence, the monetary policy rule is given by

$$\ln g_t = \left(1 - \rho_g\right) \ln \overline{g} + \rho_g \ln g_{t-1} + \eta \varepsilon_{z;t} + \varepsilon_{g;t} \tag{28}$$

where $g_t = M_t / M_{t-1}$ is the growth rate of money and $\varepsilon_{g;t} \sim N(0; \sigma_g^2)$ is the true (serially-uncorrelated) monetary policy shock. As discussed below, the fact that the monetary authority accommodates technological shocks may be motivated by its desire to stabilize prices, output, or employment.

3.4 The representative financial intermediary

Financial intermediaries are supposed to act in a perfectly competitive loans market. At the beginning of period t, the representative financial intermediary receives deposits S_t from the households and new cash injections X_t from the monetary authority. It then lends its total amount of deposits $S_t + X_t$ to the firms at the gross interest rate R_t. At the end of the period, firms pay back their loans, and the financial intermediary remunerates households' deposits at the interest factor R_t. It then makes a profit $F_t = R_t X_t$, which it redistributes to the representative household via dividend payments.

3.5 Symmetric equilibrium

In the symmetric equilibrium, all agents take the same decisions so that $P_t^i = P_t; H_t^i = H_t; K_t^i = K_t; Y_t^i = Y_t$ and $I_t^i = I_t$ for all $i \in [0; 1]$. Then, using (25), equations (20), (22), (26) and (27) may be rewritten as

$$Y_t = K_{t-1}^{\alpha} (z_t H_t)^{1-\alpha} - z_t \varphi \tag{29}$$

$$K_t = (1 - \delta) K_{t-1} + I_t \tag{30}$$

$$\left[1 - \phi_P \left(\frac{P_t}{P_{t-1}}\right)\left(\frac{P_t}{P_{t-1}} - \pi\right) - \theta \left(1 - \frac{W_t H_t}{(1-\alpha) P_t Y_t}\right)\right] Y_t + E_t \left\{\frac{1}{R_{t+1}} \phi_P \left(\frac{P_{t+1}}{P_t}\right)^2 \left(\frac{P_{t+1}}{P_t} - \pi\right) Y_{t+1}\right\} = 0 \tag{31}$$

and

$$P_t R_t = E_t \left\{\frac{1}{R_{t+1}} \left[\frac{\alpha}{1-\alpha} \frac{W_{t+1} H_{t+1}}{K_t} + (1-\delta) P_{t+1} R_{t+1}\right]\right\} \tag{32}$$

The aggregate resource constraint is

$$Y_t = C_t + I_t + \frac{\phi_p}{2} \left(\frac{P_t}{P_{t-1}} - \pi\right)^2 Y_t \tag{33}$$

Furthermore, substituting for Π_t and F_t in (13) yields

$$M_t = P_t Y_t - \frac{\phi_p}{2} \left(\frac{P_t}{P_{t-1}} - \pi\right)^2 Y_t \tag{34}$$

Equations (15), (16), (29)-(34), and the driving processes (21) and (28) form a dynamic system of 10 equations in the 10 variables Y_t, K_t, H_t, I_t, C_t, P_t, W_t, R_t, M_t and z_t, whose solution characterizes the symmetric general equilibrium of the economy.

3.6 Resolution

A problem that arises with the dynamic system in section 3.5 is that, because of the unit root present in the technological process, it involves non-stationary variables. Hence, this precludes the direct application of standard linearization techniques[14]. A well-known solution to this problem is to apply some stationary-inducing transformation to the variables, and then to

[14] King, Plosser and Rebelo (1988), and King, Plosser, Stock and Watson (1991) show that the unit root contained in the technological progress generates a common stochastic trend in most real variables such as output, consumption, investment or the capital stock. In addition, here, this stochastic component in technology implies that there is also a unit root in several nominal variables such as the price level, which can be seen for example from equation (34).

solve around the modified dynamic system involving these new variables (see King, Plosser and Rebelo, 1988). In Dufourt (1999), I show how to pursue a similar strategy by rewriting the system in section 3.5 directly in terms of the Beveridge-Nelson cyclical component of every variable. Since these components are covariance-stationary, this operation generates a new dynamic system (equivalent to the former) that now have a well-defined stationary states around which one can linearize the Euler equations. One then obtains a linear rational-expectation model for the BN cyclical component of the variables which can be solved using traditional resolution methods in the spirit of Blanchard and Kahn (1980), and notably Sims (1999)[15]. In the end, I get a simple solution that can be written in a traditional state-space form of the type

$$X_t = AX_{t-1} + B\varepsilon_t + C\varepsilon_{t+1} \tag{35}$$

where

$$X_t = \begin{bmatrix} \tilde{y}_t \\ \tilde{c}_t \\ \tilde{h}_t \\ \vdots \end{bmatrix}$$

is a vector composed of the BN cyclical component of the (log) variables, as defined in eq. (2).

Having obtained this state-space form solution (35) to the dynamic system in section 3.5, it is then relatively straightforward to calculate both analytically and by numerical simulations the implied second-order moments for these BN cyclical components.

4 Results

4.1 Calibration

The model of section 3 contains 13 exogenous parameters that are calibrated according to estimates from other studies. Specifically, parameters β, α, δ, θ_z, h and σ_z (where h is the proportion of hours worked in the stationary state) are calibrated according to King, Plosser and Rebelo (1988), whose estimates are used as reference in many studies on DGE models. The average markup is set at $\mu = 1.4$, which is the value recommended by Rotemberg

[15] See Dufourt (1999) for an extensive treatment of all that procedure, as well as for computer codes implementing the solution in terms of the Beveridge-Nelson cyclical component of the variables.

Table 4 - Cyclical properties of the RBC model

	Relative standard deviations with output ¾x/¾y								
Variable (x)	y	c	h	q	R	p	¼	m	g
Data	1	0.57	0.49	0.85	0.25	1.86	0.14	2.10	0.22
Model	1	1.26	0.20	1.19	0.03	0.96	0.16	0.09	0.06
	Cross correlations with output Corr(y; x)								
Variable (x)	y	c	h	q	R	p	¼	m	g
Data	1	0.95	0.53	0.87	0.68	-0.23	0.31	-0.60	0.32
Model	1	0.99	-0.98	0.99	-0.70	-0.99	0.36	0.48	-0.48

and Woodford (1995). The …xed-cost Á is chosen so as to ensure that …rms' pro…ts are null in the steady state. Parameters governing the monetary policy rule are set at their estimated values, that is g = 1:015, $½_g$ = 0:60, ´ = 0:1, and $¾^2_{²g}$ = 0:82. In addition, for the versions of the model in which there are price rigidities, I will impose a value of $©_p$ = 40, which is the value suggested by Ireland (1997b). Obviously, this value imposes a strong degree of sluggishness in nominal prices. In my experiments, however, it implied that the costs associated with price changes are inferior to 3% of …rms' pro…ts, which remains a reasonable assumption.

4.2 Results for the RBC model

Early RBC theorists argued that a simple stochastic growth model perturbed by technological shocks only can reproduce most features of US postwar business cycle, at least with respect to real variables. To assess the performance of the RBC model within the framework of section 3, I only have to impose a null variance for the monetary disturbance (so that only technology shocks account for the computed moments), and a null value for $©_p$ to ensure that prices adjust freely to their optimal level. Results from that experiment are reported in Table 4. From this table, it is clearly apparent that the RBC model fails dramatically at reproducing the overall pattern of US ‡uctuations. Indeed, several anomalies appear forcefully. In particular, and contrarily to the data,

1) the RBC model implies that consumption (detrended with BN) is more volatile than detrended output. From Table 4, the relative standard deviation with output is 1.26, while it was found to be 0.57 for US data.

2) the RBC model implies that (detrended) productivity is more volatile than (detrended) output. However, in the data, the actual relative standard deviation is estimated at 0.85.

3) the RBC model implies that detrended prices are about as volatile as detrended output, while they are much more volatile in US economy (the empirical relative standard deviation is as high as 1.86).

4) the RBC model implies that the money level is much less volatile than output (the theoretical relative standard deviation is 0.09), while it was estimated to be twice as volatile as output in US data.

In addition, considering now the contemporaneous cross-correlations, one can see that

5) the correlation between output and hours worked has the wrong sign. According to the model, the cyclical component of hours is strongly countercyclical, while it is procyclical in US economy.

6) the correlation between the interest rate and output has the wrong sign (the model predicts a negative correlation of -0.70, while it is estimated at 0.68 in the data)

7) the correlation between money growth and output has the wrong sign. According to the model, money growth and output are negatively correlated, while the opposite holds in US data.

8) the correlation between the money level and output has also the wrong sign. The model's prediction is that both series are procyclical, while the data suggest they are strongly countercyclical.

Points 1 and 5 have been used by Rotemberg and Woodford (1996) to criticize the standard RBC model. However, Table 4 shows that there are many other dimensions along which this model fails as well. In fact, neither the behavior of the nominal nor the real variables seem to be adequately described by the RBC model.

To understand the origins of these failures, it is useful to look at the plots reported in figure 4. Figure 4 displays the theoretical BN cyclical components of most macroeconomic variables for the first ten periods following a 1 percent point increase in technological conditions. Note that, for variables that contain a unit root, these plots differ from the traditional impulse response functions in that they do not represent the time evolution of a variable after a shock, but instead the difference between the current value of this variable and its anticipated long-run level (as is consistent with the definition

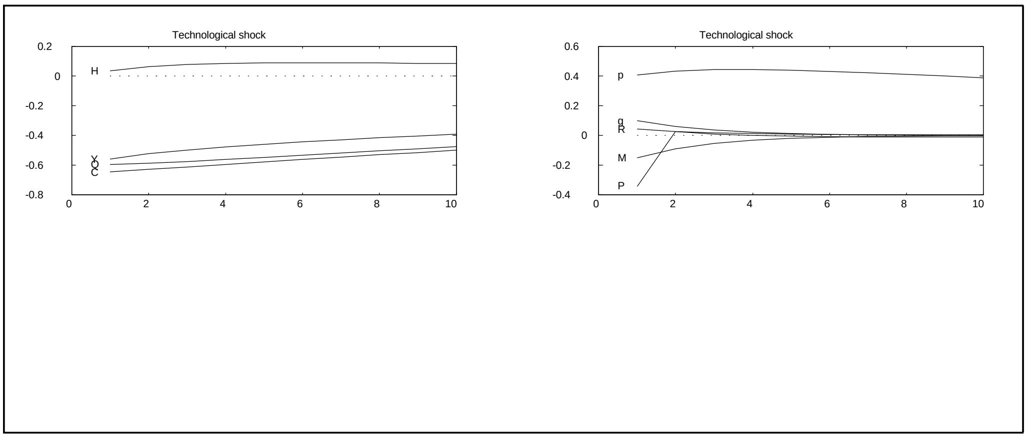

Figure 4: Cyclical components for the RBC model

of Beveridge and Nelson)[16]. Hence, figure 4 shows that after a permanent increase in production possibilities, consumption, output and productivity all approach their long-run level from below, so that their BN cyclical components are negative. As emphasized by King, Plosser and Rebelo (1988), this gradual expansion occurs because the specification of consumers' preferences implies that there are intertemporal substitution effects which incite the agents to smooth consumption's variations over time. Furthermore, all three series being forecasted to move in the same direction, it is natural to expect that their cyclical components be positively correlated. Table 4 confirms that intuition by reporting cross-correlations between these series as high as 0.99[17]. Since the actual correlations in these series are also very high, one may be tempted to conclude that the RBC model performs well at explaining the pattern of US fluctuations, at least for these three variables.

However, figure 4 also shows that, during the periods following the technological shock, productivity and consumption converge more slowly to their

[16] As I recalled in footnote (8), linearly detrended stationary variables are not affected by the BN procedure.

[17] In Dufourt (1999), it is shown that the theoretical cross-correlation in the BN cyclical component of most macroeconomic variables is even perfect (one in absolute value) when there are no monetary accommodation of technology variations. The reason is that, in such a framework, all the forecastable movements in these variables can be considered as resulting from the variations in a single parameter, the discrepancy between the actual capital stock and its expected long-run level. However, allowing monetary authorities to accommodate technological shocks breaks this perfect correlation by inducing shifts in the money level that tend to persist over time (see figure 4). These persistent shifts in the money level generate in turn specific forecastable movements that are no longer perfectly correlated with those resulting from the initial change in productivity conditions.

long-run level than output. As a result, the forecastable components of consumption and productivity have a larger variance than the forecastable component of output, and Table 4 consistently reports relative standard deviations ratios above unity. These predictions of the model are not validated by the data, since detrended consumption and productivity are in fact less volatile than detrended output in US economy. Hence, the model-implied cyclical part of output, consumption and productivity have a somewhat different as their counterparts in the data.

Now consider the behavior of hours worked. As in King, Plosser and Rebelo (1988), hours worked increase in response to technological expansions[18]. But since labor is a trend-stationary variable, this increase is expected to be temporary and hours are forecasted to come back to their initial level in the future. As a result, the cyclical component of hours is positive, and its correlation with detrended output is necessarily negative. It is this counterfactual result which was at the heart of Rotemberg and Woodford's criticism towards the RBC model.

Consider now the behavior of the nominal variables. Results for the monetary aggregates can be easily understood by looking similarly at the plots reported in …gure 4: First, because monetary authorities accommodate technology improvements, the money growth rate is increased by 10 percent the original increase in technology. But as this increase is transitory, the money growth rate is expected to revert back to its original level in the in…nite future, and its cyclical component is therefore positive. However, money growth variations being also persistent, the level of money is predicted to continue rising even after its …rst period expansion. As a result, money is below its long-run level, so that its cyclical component is negative. Overall, the model's predictions are then that the money growth rate is expected to decrease when output and the money level are expected to increase. Table 4 consistently reports a negative correlation between the BN cyclical components of output and money growth (-0.48), and a positive correlation between the cyclical parts of output and the money level (0.48). But as Table 4 recalls, these predictions of the RBC model are again at odds with US data, since the actual correlations are of the other sign (they are respectively given by 0.32 and -0.60). In addition, the size of the forecastable component of money generated by the model is far too small, since the theoretical relative standard deviation with output is only 0.09, while it was estimated at 2.10 in US data.

The behavior of in‡ation, the price level, and the nominal interest factor

[18] Of course, the presence of imperfect competition and monetary accommodation implies that this increase is much weaker than in the perfectly competitive framework.

are more complicated combinations of the e¤ects generated by the variations in technological conditions and the monetary accommodation of these variations. In the absence of any accommodation by the monetary authorities, the money-output equation (18) would imply that any expansion in output should be automatically reported on the price level. Hence, if output was predicted to rise gradually by 1%, the price level would be predicted to decline gradually by the same amount. However, the activist rule followed by the monetary authorities breaks this symmetrical pattern, since the gradual injection of new cash in the economy prevents a large part of the fall needed in the price level to accommodate output's expansion. Nevertheless, for the reference calibration used here, this e¤ect is su¢ciently small so that it doesn't change the qualitative feature of the cyclical component of prices: After a technology improvement, the in‡ation rate temporarily falls, and the price level remains expected to decline in the long-run. Hence, the cyclical component of prices is negatively correlated with output, while the correlation between in‡ation and output is positive. If these correlations are not inconsistent with the data, the relative volatilities between these series are not reproduced: In the data, the cyclical component of prices is twice as volatile as output (the estimated ratio is 1.86), while the theoretical ratio is only 0.96.

Finally, …gure 4 shows that the nominal interest factor increases after the rise in technology. Being stationary, this rate is also expected to decline in the future, so that its cyclical component is negatively correlated with those of output. Again, this prediction is inconsistent with the data, the actual correlation being strongly positive (+0.68). Hence, the RBC model cannot either reproduce the correct pattern of ‡uctuations for this variable.

4.3 Results for the NCE model

In the NCE model, prices are perfectly ‡exible but both technological and monetary shocks a¤ect the economy. There are two main reasons for introducing monetary disturbances into the ‡exible price model studied in the last section. First, there exists a vast empirical literature which documents that actual monetary policy is submitted to important stochastic variations, and taking this fact into account is important if one wishes to give a realistic description of the real economy. Second, this other source of disturbance is at the origin of speci…c forecastable movements in macroeconomic variables that are of di¤erent nature than those resulting from technology variations. By making abstraction of this source of disturbance, one could therefore be led to wrongly reject the ‡exible price model, even if its underlying structure was correct.

Table 5 - Cyclical properties of the NCE model

	Relative standard deviations with output $\frac{\sigma_x}{\sigma_y}$								
Variable (x)	y	c	h	q	R	p	π	m	g
Data	1	0.57	0.49	0.85	0.25	1.86	0.14	2.10	0.22
Model	1	1.16	0.47	1.10	0.23	1.03	0.83	0.92	0.62

	Cross correlations with output $Corr(y; x)$								
Variable (x)	y	c	h	q	R	p	π	m	g
Data	1	0.95	0.53	0.87	0.68	-0.23	0.31	-0.60	0.32
Model	1	0.94	0.01	0.90	-0.46	-0.49	-0.29	0.43	-0.43

To understand why this is so, consider for example the forecastable components of output and hours worked generated by a transitory increase in the money growth rate (see figure 5). In this model, because inflation acts as a tax on consumption's good, the consumer's optimal choice is to substitute consumption for leisure, and then to reduce labor and output in the short-run. However, since money is neutral in the long-run, these declines are expected to be transitory, and both variables are predicted to come back up to their initial level in the future. Hence, the predictable movements in output and hours that result from monetary disturbances are positively correlated, and this positive correlation may be strong enough to offset the negative correlation implied by technology variations. By neglecting the contribution of monetary policy shocks, one simply forces the model to generate a counterfactual result which would not necessarily appear in the more general framework.

A similar analysis can be applied for the cyclical components of consumption and productivity: figure 5 shows that, contrarily to the case of technology disturbances, monetary policy shocks generate predictable movements in these variables that have a smaller amplitude than the forecastable movements in output. One may therefore expect that taking these shocks into account could reduce the relative standard deviation of these variables, and then to improve the predictions of the flexible price model over this dimension as well.

However, Table 5 shows that only partial support can be given to these assertions, and the NCE model remains importantly failing over most features of US business cycle. As expected, the NCE model succeeds in generating a slightly positive correlation between detrended output and hours (the theoretical correlation is 0.01), but this correlation remains very far from the

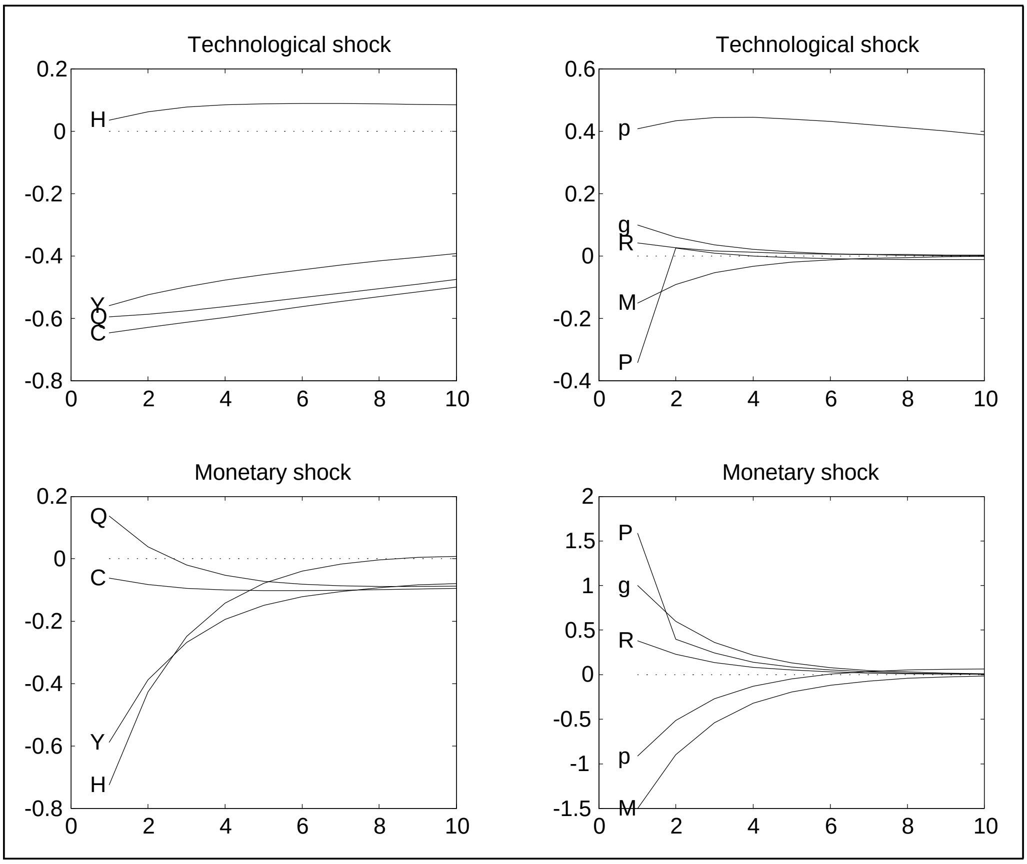

Figure 5: Cyclical components for the NCE model

estimated value of 0.53. Furthermore, the relative standard deviations of consumption and productivity with output are somewhat reduced, but the size of this reduction is far too small since both ratios remain counterfactually above unity. Of course, it would still be possible to improve further these results by raising arbitrarily the variance of the monetary disturbance. But this proceeding would clearly be arbitrary. Furthermore, it would still be useless to solve several other of the wrong predictions made by the ‡exible price model.

In fact, …gure 5 illustrates why the NCE model is structurally unable to account for several stylized facts reported in section 2, such as the positive correlation between output and money growth, the negative correlation between output and the money level, and the positive correlation between output and the nominal interest rate. For example …gure 5 shows that, in addition to the drop in output, a one percent increase in the money growth rate generates a transitory increase in the nominal interest factor, and a permanent and gradual increase in the money level. Hence, output and the money level are expected to move in the same direction, while money growth and the interest rate are expected to move in the opposite direction. The consequence is that, as was the case with technology variations, the correlations implied by monetary policy shocks have the wrong sign: Whatever the variance of the monetary disturbance, the NCE model will therefore fail at accounting for the empirical correlations. In that sense, these failures can be thought as 'structural'.

Finally, having reviewed the dimensions for which the NCE model does not perform better than the purely real model, one could even stress some for which it does even worse. As an example, if the RBC model was correct at predicting a positive correlation between output and in‡ation, the NCE model now implies the opposite (the positive correlation resulting from technology variations being more than o¤set by the negative correlation generated by monetary disturbances). Similarly, while the RBC model was correct at generating an in‡ation to output ratio of 0.16, the NCE model now predicts a too high value of 0.83.

In light of all these results, it seems hard to consider that the NCE model provides a description of the business cycle that is in general agreement with the observed pattern of US ‡uctuations, at least when these ‡uctuations are considered under the view of the BN …lter. Table 5 recalls that there are too many dimensions for which the NCE model make opposite predictions. Of course, some of these failures could probably be overturned by changing some aspects or shortcomings of the model, but in my view these failures are numerous and serious enough to cast doubts on the NCE model as a whole.

4.4 Results for the NNS model

In the NNS model, technology and monetary shocks hit the economy, but …rms face convex costs of adjusting their price. The sticky price version of business cycle models has long been advocated by some (but not all) macroeconomists as a good challenger to the ‡exible price model for explaining the patterns of US ‡uctuations, and particularly the relationships between the real and nominal variables. It is therefore natural to test its ability within the framework retained in this paper. Table 6 displays the results from that experiment. It appears that the NNS model does a very good job at accounting for the most important features of US business cycle. In fact, its succeeds over nearly all the dimensions for which the two ‡exible prices models su¤ered salient failures.

Figure 6 …rst shows that the presence of price rigidities does not really

Table 6 - Cyclical properties of the NNS model

	Relative standard deviations with output $\frac{\sigma_x}{\sigma_y}$								
Variable (x)	y	c	h	q	R	p	π	m	g
Data	1	0.57	0.49	0.85	0.25	1.86	0.14	2.10	0.22
Model	1	0.91	0.64	0.82	0.19	1.29	0.20	0.52	0.34
	Cross correlations with output $Corr(y; x)$								
Variable (x)	y	c	h	q	R	p	π	m	g
Data	1	0.95	0.53	0.87	0.68	-0.23	0.31	-0.60	0.32
Model	1	0.90	0.58	0.77	0.61	-0.93	0.71	-0.39	0.39

alter the way the economy responds to technology shocks (even if there are differences in magnitudes): After a one percent permanent increase in technology conditions, output, consumption and productivity still converge to their new long-run level from below, while prices gradually decline to their new steady state. Furthermore, the money growth rate is temporarily increased to accommodate this technology expansion, and this generates in turn a gradual rise in the money level. One notable difference, however, is that hours worked now decline in the short-run. The reason is that monetary accommodation is to weak to ensure an expansion in real balances (and thus, in aggregate demand) sufficient to allow a strong increase in production. Instead, firms meet this relatively weak demand by reducing their labor input. The mechanism there is identical to those in Galí (1999) or Basu et al. (1998), and is consistent with the empirical finding by these authors of a negative response of hours worked to an increase in total factor productivity.

Still, except for the correlation between output and hours, one cannot expect that the structure of economic fluctuations be significantly changed by considering only technological shocks, even in an environment where prices are sticky. In fact, figure 6 shows that the most significant changes will come from adding monetary disturbances. Indeed, while a one percent rise in the money growth rate generates cyclical components of the nominal variables that are qualitatively the same as in the NCE model, the important difference is that output, consumption and hours worked now increase in the short run. Money being neutral at long horizons, they are next expected to decline in the future. These changes in the expected paths of the real variables have several important implications: First, by opposition to the NCE model, the sticky price model implies that the forecastable movements in consumption, output and hours worked are positively correlated for both types of disturbances,

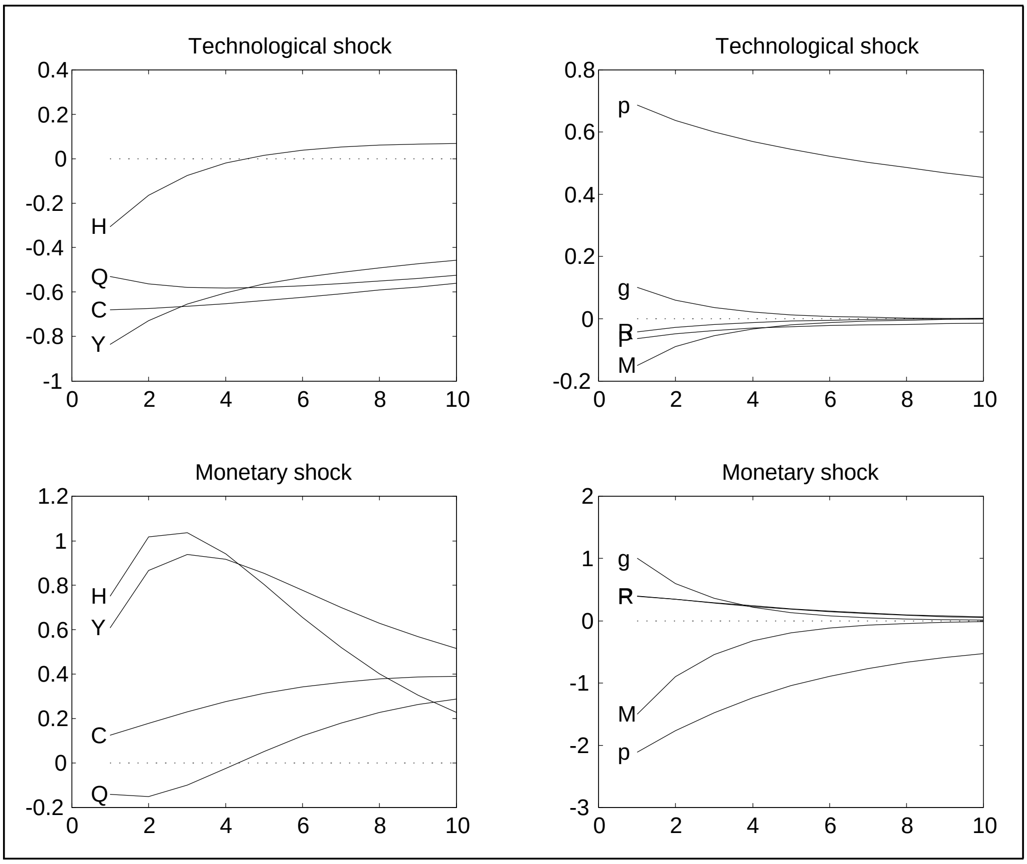

Figure 6: Cyclical components for the NNS model

and this could potentially help solving the empirical puzzle identi…ed by Rotemberg and Woodford in this respect. Second, since the nominal variables are expected to move as in the NCE model, but that output is predicted to move the opposite direction, the correlations between output and the nominal variables conditional on monetary disturbances will have the opposite sign as in the NCE model. It is therefore perfectly possible that these correlations dominate the wrong correlations resulting from technology variations.

Tables 6 shows that this is indeed the case. In conformity with the above analysis, the NNS model is able to match closely the positive correlation between the cyclical components of output and hours (the theoretical correlation of 0.58 is very close to the estimated value of 0.53), and to account for the procyclical behavior of in‡ation, the interest rate, and the money growth rate. It is also able to reproduce the negative correlation between output and the money level. All these correlations were very badly explained by the two ‡exible price models. Furthermore, and also in contrast with the previous models, the NNS model is able to account for the small volatilities of consumption and productivity relative to output (the ratio of standard deviations are consistently below unity), while reproducing the stronger volatility of prices.

The latter …nding deserves notably a few comments. The two ‡exible price models failed at accounting for the large variance in the cyclical component of prices because they both implied that prices adjusted too quickly to their new long-run level after each kind of disturbance. By contrast, the presence of adjustment costs in the NNS model makes this adjustment process much longer, which automatically increases the overall variance in the forecastable component of this series relative to that of output. The resulting theoretical ratio of 1.29 is in much closer agreement with the actual ratio than the near unity value implied by the preceding models. Again, these improvements in the model's predictions are essentially due to the preponderant in‡uence of monetary shocks in an economy with sticky prices.

Finally, it should be stressed that these successes of the NNS model are obtained without deteriorating the other dimensions for which the RBC and NCE models made correct predictions. For example, the NNS model still generates high consumption-output and productivity-output correlations (some important features of the data), and account for the negative correlation between output and prices (even if this correlation is somewhat too strong). In fact, the only important failure of the NNS model apparent in Table 6 concerns the variance of money relative to output. Indeed, the theoretical ratio of 0.52 is very far from the actual value of 2.10 estimated in US data. In my view, rather than a strong argument against the NNS model, this …nding is essentially an indication that the way monetary policy is modeled in this paper is too rudimentary, and should be replaced in ongoing research by a more sophisticated rule of the type suggested by the recent literature.

5 US business cycle and characteristics of the NNS model

A central message of the RBC paradigm was that technology shocks account not only for growth (that is, changes in technology conditions that have a permanent e¤ect on the level of output), but also for a dominant part of economic ‡uctuations. This view has been recently challenged on empirical grounds by Galí (1999), who shows that the estimated high-frequencies implications of permanent productivity changes on output are poorly correlated

Table 7 - Relative contribution of money versus technology shocks to overall ‡uctuations

	Relative standard deviations with output ¾x/¾y								
Variable (x)	y	c	h	q	R	p	¼	m	g
NNS model	1	0.91	0.64	0.82	0.19	1.29	0.20	0.52	0.34
cond./money	1	0.72	0.80	0.61	0.24	1.46	0.25	0.65	0.44
cond./technology	1	1.16	0.19	1.06	0.02	0.96	0.04	0.07	0.05
	Cross correlations with output Corr(y; x)								
Variable (x)	y	c	h	q	R	p	¼	m	g
NSS model	1	0.90	0.58	0.77	0.61	-0.93	0.71	-0.39	0.39
cond./money	1	0.85	0.79	0.60	0.76	-0.93	0.81	-0.53	0.53
cond./technology	1	0.99	-0.25	0.98	0.39	-0.99	0.93	0.55	-0.55

with the periods of recessions identi…ed by the NBER.

In this section, I address a similar issue, but I focus instead on the theoretical side of this kind of analysis. Indeed, results in the last section suggested that the sticky price framework proposed in several studies provides a business cycle model which is in general agreement with the estimated features of US ‡uctuations. Hence, if this model is correct, it can be used to asses the relative contribution of demand and technology disturbances to the overall pattern of economic ‡uctuations.

I pursued this idea by performing a very informal comparison between the actual versus conditional second-order moments implied by the NNS model (see Table 7). According to that table, strong supports can be given to Galí's assessment. Indeed, the e¤ective dynamics of the business cycle is clearly much more strongly in‡uenced by monetary factors than by purely real sources of disturbances. This is easily seen by the fact that actual moments are essentially determined by those conditional on monetary disturbances. This is particularly true for the cases where the conditional correlations di¤er sharply in sign or in magnitude.

What is suggested by this informal analysis? Remind that in this model, variations in output occur for two reasons: Unpredictable movements generated by permanent shifts in the exogenous trend (because of the assumption that long-run growth is stochastic), and predictable movements resulting from the slow adjustment process to permanent and transitory disturbances. In this paper, I have argued that there is a sense in considering that only these ‡uctuations in output that are predictable should be regarded as “business cycle” phenomena. Given this interpretation, then the NNS model leads us to a very traditional picture of macroeconomic phenomena: Real factors are solely responsible for growth, while economic ‡uctuations are primarily driven by monetary disturbances. Although these results are still subject to the caveat that many other shocks remain excluded from the analysis, they cast serious doubts on the original message of the RBC paradigm.

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