GENERAL EQUILIBRIUM RESTRICTIONS FOR DYNAMIC FACTOR MODELS

2010

David de Antonio Liedo

Documentos de Trabajo
N.º 1012

BANCO DE ESPAÑA
Eurosistema

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(*) Financial support from U.L.B. is gratefully acknowledged. I also wish to thank Domenico Giannone, Romain Houssa, Pelin Ilbas, Samuel Hurtado, Alexandre Janiak, Robert Kollmann, Francesca Monti, Eva Ortega, Gabriel Pérez-Quirós, Paulo Santos Monteiro, Lucrezia Reichlin, Carlos Thomas, Alberto Urtasun, David Veredas, Philippe Weil and Raf Wouters for helpful discussions and suggestions. Peter Ireland's contribution by making his codes easily accessible is gratefully acknowledged. All errors are my sole responsibility.

Documentos de Trabajo. N.º 1012

2010

ISSN: 0213-2710 (print)
ISSN: 1579-8666 (on line)
Depósito legal: M. 19472-2010
Unidad de Publicaciones, Banco de España

Abstract

This paper proposes the use of dynamic factor models as an alternative to the VAR-based tools for the empirical validation of dynamic stochastic general equilibrium (DSGE) theories. Along the lines of Giannone et al. (2006), we use the state-space parameterisation of the factor models proposed by Forni et al. (2007) as a competitive benchmark that is able to capture weak statistical restrictions that DSGE models impose on the data. Beyond the weak restrictions, which are given by the number of shocks and the number of state variables, the behavioural restrictions embedded in the utility and production functions of the model economy contribute to achieve further parsimony. Such parsimony reduces the number of parameters to be estimated, potentially helping the general equilibrium environment improve forecast accuracy. In turn, the DSGE model is considered to be misspecified when it is outperformed by the state-space representation that only incorporates the weak restrictions.

Keywords: dynamic and static rank, factor models, DSGE models, forecasting.

JEL classification: E32, E37, C52.

1 Introduction

The general equilibrium model developed by Kydland and Prescott (1982) is currently the standard reference in Real Business Cycle (RBC) literature. This type of model describes in a very parsimonious way the representative agent's optimal decisions in response to a single technology shock. The latter induces *predictable* co-movements in the main macroeconomic aggregates as they converge towards their steady state values. Vector autoregressive (VAR) models and dynamic factor models are often used as approximate representations of the theory.

As suggested by Giannone et al. (2006), factor models are able to compete with VARs as tools to validate general equilibrium theories. The use of dynamic factor models in macroeconomics dates back three decades, starting with the paper by Sargent and Sims (1977). Factor models are relatively restrictive representations that allows us to express the data as the sum of two orthogonal components: one driven by pervasive factors that spread thoughout the economy, and a measurement error component that is idiosyncratic. In this vein, Altug (1989) proposes using a dynamic factor model to represent the observables of a simple RBC economy where technology shock is the main pervasive factor that propagates in a context of time-to-build features.

Alternatively, the VAR approximation provides a relatively unrestricted representation of the data. Since the linearised solution of a wide range of dynamic stochastic general equilibrium (DSGE) models has a vector autoregressive (VAR) representation (see, for example, Ravenna (2007) and references therein[1]), the empirical validation is often based on these statistical benchmarks. Thus, VARs are considered to be relatively unrestricted representations of the data that contribute to understanding the extent to which the DSGE cross-equation restrictions are valid.

[1] Ravenna (2007) discusses the conditions needed for a finite order VAR representation of a general equilibrium model to exist.

Thus, general equilibrium models tend to approach the performance of VARs in terms of goodness of fit in numerous applications. Ireland (2004) has shown that a relatively simple RBC model augmented with a vector of measurement errors is able to produce out-of-sample forecasts that are comparable to those of reduced form VARs. More explicit evidence on the proximity of VARs and state-of-the-art business cycle models in terms of their ability to fit the data and forecasting is provided by Del Negro, Schorfheide, Smets and Wouters (2007). More forecasting experiments where business cycle models successfully compete with different VAR benchmarks provide similar results (e.g. Smets and Wouters (2007) for the US, Smets and Wouters (2004) for the euro area, or Adolfson et al. (2008) for Sweden).

In this paper, we compare the out-of-sample forecasting performance of a simple RBC model augmented with a serially correlated noise component against several specifications belonging to the class of dynamic factor models, which also incorporate noise, and alternative models belonging to the VAR class. We exploit the parameterisation of the factor models proposed by Forni et al. (2007), which allows us to capture some of the key *statistical restrictions* that DSGE models may impose on the data: dynamic and static rank. The *dynamic rank* of a general equilibrium model is equal to the number of shocks and determines the rank of the spectral density of the endogenous variables. In turn, the *static rank* determines the complexity of the transmission mechanism of the shocks, placing an upper bound on the rank of the covariance matrix of variables specified in the model. While Altug (1987) acknowledges the first feature, the parameterisation of the factor models used here enables incorporating both the static and dynamic rank restrictions.

Our results are in line with the favorable forecasting properties of DSGE models obtained in previous literature. The RBC model's performance is comparable to that of the reduced form models considered in this paper, and even outperforms all in terms of mean-squared-error at forecasting consumption. Thus, the behavioural assumptions embedded in the utility and production functions of the model economy contribute to achieving simplicity. Such parsimony reduces the number of parameters to be estimated, helping the general equilibrium environment achieve forecast accuracy.

A formal test of significance, based on Hansen et al. (2007), is useful to further interprete our results. The test suggests that the rank reduction restriction embedded in the RBC model happens to be a desirable property that contributes to forecasting. This conclusion is drawn from the fact that the dynamic factor model with the same number of shocks and states as the RBC model is among the subset of *best* forecasting models for all variables and horizons. In contrast, the RBC model itself is not always among the subset of best forecasting models, which questions the forecasting properties of its behavioral assumptions.

These results reconcile the critiques of Rotemberg and Woodford (1996) against RBC models with the more encouraging results obtained by Ireland (2004) and by Ingram and Whiteman (1994). In spite of the potential level of misspecification present in RBC models, we conclude that the dimension of their state-space representation provides weak restrictions that improve forecasting.

This paper is organised as follows. In Section 2, we describe the parametric space in which VARs, factor models and RBC models are contained, followed by a presentation of their forecasting performance, in Section 3. The conclusions drawn in this section are formally tested in Section 4. Finally, in Section 5 we conclude that dynamic factor models are a useful tool for the empirical validation of equilibrium business cycle models. In particular, these models contribute to our understanding of the extent to which micro-founded behavioral restrictions add value beyond the parsimony achieved through the rank restrictions.

2 The Set of Models and their Implied Restrictions

Here we clarify the types of restrictions that the class of dynamic factor models (DFMs) can borrow from the RBC model. Drawing on Giannone et al. (2006) and Forni et al. (2007), we define the classes of dynamic factor models and general equilibrium economies in terms of the key features that determine their complexity.

2.1 A Prototypical Business Cycle Model

This subsection describes a simple RBC model that explains the joint behaviour of output, consumption, investment and hours worked. In this prototypical model, the Business Cycle is generated by the efficient response of agents to a single shock: technology. All the details of this model can be found in Hansen (1985), Ireland (2004) and the references therein.

In models of this type, a representative consumer with defined preferences regarding consumption C_t and hours worked H_t faces the problem of maximising the following intertemporal utility function:

$$E\sum_{t=0}^{\infty}\beta^t\left[ln(C_t)-\gamma H_t\right]$$

where $\beta^t \in (0,1)$ is a discount factor and $\gamma > 0$.

On the production side of the economy there is a constant-returns-to-scale technology:

$$Y_t = A_t K_t^{\theta}(\eta^t H_t)^{1-\theta}$$

where $\eta > 1$ implies a deterministic trend on Y_t and where $1 > \theta > 0$. A_t is the state of technology, which is exogenous in this model economy.

The following identities provide the model with logical coherency. First, the consumer divides output between consumption and investment: $Y_t = C_t + I_t$. This means that the consumption and investment time series are added up to match the concept of output implied by the model. Alternatively, an exogenous spending shock could be introduced in this equation to capture government expenditure and net exports, making it possible to use real GDP in the estimation of the model.

The second identity is an accumulation equation for capital that depreciates at a rate $1 > \delta > 0$: $K_{t+1} = (1-\delta)K_t + I_t$.

The cycle in this model is generated by an exogenous stochastic process that determines the time-varying parameter A_t in the production function:

$$ln(A_t) = (1-\rho)ln(A) + \rho ln(A_t) + \epsilon_{\mathrm{t}}$$

where $\rho \in (-1, 1)$.

Once the first order conditions that define the behaviour of agents in this economy are obtained (see Ireland (2004) for a description[2]), and defining $y_t = Y_t/\eta^t$, $c_t = C_t/\eta^t$, $i_t = I_t/\eta^t$, $k_t = K_t/\eta^t$, $h_t = H_t$ and $a_t = A_t$, the new system is log-linearized around the steady state. Using standard procedures, the model solution is obtained and represented recursively in state-space form:

$$\mathrm{Y_t} = \Lambda_{3\times 2}(\vartheta)\mathrm{X_t} \quad (1)$$

$$\mathrm{X_t} = \Phi_{2\times 2}(\vartheta)\mathrm{X_{t-1}} + B(\vartheta)\epsilon_t \quad (2)$$

where $\mathrm{Y_t} = \begin{pmatrix} \hat{y}_t \\ \hat{c}_t \\ \hat{h}_t \end{pmatrix}$ and $\mathrm{X_t} = \begin{pmatrix} \hat{k}_{t-1} \\ \hat{a}_t \end{pmatrix}$. This is a very common representation of a general equilibrium model solution. The state vector, $\mathrm{X_t}$, contains endogenous predetermined variables and exogenous variables. Furthermore, this formulation emphasizes the dependence of the coefficients matrices on the RBC model parameters $\vartheta = \{\beta, \eta, \theta, \rho, \delta\}$:

[2] The Note “Matlab code for A Method for Taking Models to the Data” contains all the derivations.

The vector of observables includes endogenous non-predetermined variables, but it could as well include other endogenous or exogenous variables for which data is available.

2.2 VARs

Starting from the state-space form of the RBC model (1-2), the derivation of a VAR representation is straightforward. First, expression (2) is written as:

$$\mathrm{X_t} = (I_{2\times 2} - \Phi_{2\times 2}(\vartheta)L)^{-1}B(\vartheta)\epsilon_t \tag{3}$$

Substituting this expression in equation(1), and defining the pseudo inverse of $\Lambda_{3\times 2}$ as $\widetilde{\Lambda}_{2\times 3}(\vartheta) = (\Lambda_{2\times 3}\Lambda_{3\times 2})^{-1}\Lambda_{2\times 3}$, we can easily derive the VAR form of our observables:

$$\begin{aligned}
\mathrm{Y_t} &= \Lambda_{3\times 2}(\vartheta)(I_{2\times 2} - \Phi_{2\times 2}(\vartheta)L)^{-1}B(\vartheta)\epsilon_t \\
\widetilde{\Lambda}_{2\times 3}(\vartheta)\mathrm{Y_t} &= \underbrace{\widetilde{\Lambda}_{2\times 3}(\vartheta)\Lambda_{3\times 2}(\vartheta)}_{I_{2\times 2}}(I_{2\times 2} - \Phi_{2\times 2}(\vartheta)L)^{-1}B(\vartheta)\epsilon_t \\
(I_{2\times 2} - \Phi_{2\times 2}(\vartheta)L)\widetilde{\Lambda}_{2\times 3}(\vartheta) &= B(\vartheta)\epsilon_t \\
\Lambda_{3\times 2}(I_{2\times 2} - \Phi_{2\times 2}(\vartheta)L)\widetilde{\Lambda}_{2\times 3}(\vartheta) &= \Lambda_{3\times 2}B(\vartheta)\epsilon_t
\end{aligned}$$

This implies that:

$$(I - \Psi_{3\times 3}(\vartheta)L)\mathrm{Y_t} = w_t \tag{4}$$

where $\Psi_{3\times 3}(\vartheta) = \Lambda_{3\times 2}\Phi_{2\times 2}(\vartheta)\widetilde{\Lambda}_{2\times 3}$ and $w_t = \Lambda_{3\times 2}B(\vartheta)\epsilon_t$.

Note that the VAR coefficient matrix also depends on ϑ, as made explicit by our notation. Thus, the dynamics of the RBC model can be captured by a VAR(1) representation. This idea was used by Ingram and Whiteman (1991) to extract prior information from the RBC model and impose it on a VAR.

However, if the data generated by a general equilibrium model are actually published by the statistical agency with measurement errors, the representation of the observed data keeps the VAR(1) component, $\Psi_{3\times3}(\vartheta)$, but adds in an MA(1) term, making it impossible to obtain a consistent estimate of $\Psi_{3\times3}(\vartheta)$. Approximating the VARMA(1,1) by means of a VAR(p^*) with $p^* > 1$ is always possible, but the approximation error will depend on two factors: the variance of the noise component and the persistence of the original VAR(1) representation. It may also depend on the persistence of the measurement error process when this presents serial correlation[3].

2.3 Dynamic Factor Models

An unobservable index model of the type described by Sargent and Sims (1977) can be represented along the lines of Forni et al. (2007) to make the mapping between general equilibrium and dynamic factor models more explicit.

In factor models, the variables of interest are expressed as the sum of two independent components: the "common component", χ_t, which captures the variance induced by aggregate macroeconomic shocks, ϵ_t^f, and an "idiosyncratic component", ξ_t, which represents variable specific dynamics or noise:

$$\underbrace{\mathrm{Y_t}}_{n\times1} = \underbrace{\chi_t}_{n\times1} + \underbrace{\xi_t}_{n\times1} \tag{5}$$

$$\underbrace{\chi_t}_{n\times1} = \underbrace{B(L)}_{n\times q}\underbrace{\epsilon_t^f}_{q\times1} \tag{6}$$

The filter $B(L)$ determines the impulse response functions and ϵ_t^f is assumed to be orthogonal to the vector of variable specific measurement errors ξ_t. Following Forni et al. (2007), the static representation of the above described factor model can be obtained by assuming $B = AN(L)$, where A is a $n \times r$ and $N(L)$ is a $r \times q$

[3] If for example, the measurement errors follow an AR(1) process and the true data has a VAR(1) representation, the dynamics of the *observed* data can be captured with a VAR(2) component and two MA(1) terms. Thus, the VAR(p^*) approximation error depends on the eigen values associated to both the VAR(1) and the AR(1) processes

matrix polynomial (with $r \leq q$). Thus,

$$\mathrm{Y_t} = Af_t + \xi_t \quad (7)$$

$$f_t = N(L)\epsilon_t^f \quad (8)$$

where the $r \times 1$ vector of static factors f_t, the filter $N(L)$, matrix A and the structural shocks ϵ_t^f are not identified[4]. One controversial assumption made by these authors is that there exists a $q \times r$ one-sided filter $G(L)$ such that $G(L)N(L) = I_q$, that is, ϵ_t^f can be recovered from the present and past of the common component[5]. This means that equation (10) can be approximated by a VAR representation of the static factors. The VAR(p) representation, with $p = 1$ for simplicity, could be written as follows: $f_t = Df_{t-1} + R\epsilon_t^f$, where R is a $r \times q$ matrix such that $N(L) = (I - DL)^{-1}R$.

In the Section 3 we describe the identification hypothesis used to estimate all the parameters of the dynamic factor model, which we parameterise in terms of the following equation:

$$\mathrm{Y_t} = Af_t + \xi_t \quad (9)$$

$$f_t = Df_{t-1} + R\epsilon_t^f \quad (10)$$

The state-space representation of the dynamic factor model (9-10) is very similar to that of the Real Business Cycle Model (1-2) when the measurement equation (1) is augmented with a vector of idiosyncratic error terms. In the next subsection we provide a more detailed description of the mapping between general equilibrium theories and dynamic factor models.

[4]If $g_t = Gf_t$, where G is $r \times r$ invertible, then $y_t = [AG^{-1}]g_t + \xi_t$, with $g_t = [GN(L)]\epsilon_t^f$ is another static representation for $\mathrm{Y_t}$.

[5]This assumption receives the name of *fundamentalness*. Forni et al. (2007) argue that under the assumption that the number of observables n is larger than the number of shocks q, non fundamentalness is more unlikely to happen. The same idea is illustrated by Giannone and Reichlin (2007) in an empirical study of the effects of technology shocks in hours worked.

2.4 RBC-DFM Mapping

In this subsection we define a mapping between the dynamic factor analytical structure (10-9) and general equilibrium models such as that defined by expressions (1-2). Both recursive representations of the data have the same analytical structure if a vector of idiosyncratic disturbances is added in the measurement equation of the RBC model (1). Therefore, one may consider imposing restrictions coming from the RBC model onto the dynamic factor representation (10-9). Note that the *static rank* r of the dynamic factor model, which is defined as the length of the vector of static factors f_t, may be set equal to the dimension of X_t, while the *dynamic rank* of the factor model, which is given by the dimension of ϵ_t^f, may be set equal to the number of structural shocks in the RBC model[6]. Given the good forecast accuracy of a simple RBC model documented by Ireland (2004), the *size* of its state-space representation can be used to restrict r and q.

Defining Static and Dynamic Rank

The solution of business cycle models can be writen in more general terms with the following recursive structure:

$$\begin{aligned} \Psi(L)s_t &= \epsilon_t \\ C(L)x_t &= D(L)s_t \\ \mathrm{Y_t} &= \Lambda_1(L)x_t + \Lambda_2(L)s_t \end{aligned}$$

where x_t is the $m \times 1$ vector of endogenous predetermined variables and s_t is the $q \times 1$ vector of exogenous variables. The "dynamic rank" of the model is given by q. This parameter is equal to the number of structural shocks, and determines the rank of the spectral density of the model.

[6] An alternative mapping between DSGE and dynamic factor models is explored by Baurle (2008)

The complexity of the model is given by the length of the filters:

$$\begin{aligned} C(L) &= C_0 + C_1 L + \ldots + C_{p_c} L^{p_c} \\ D(L) &= D_0 + D_1 L + \ldots + D_{p_d} L^{p_d} \\ \Lambda_1(L) &= \Lambda_{1,1} L + \ldots + \Lambda_{1,p_{\Lambda_1}} L^{p_{\Lambda_1}} \\ \Lambda_2(L) &= \Lambda_{2,0} + \Lambda_{2,1} L + \ldots + \Lambda_{2,p_{\Lambda_2}} L^{p_{\Lambda_2}} \end{aligned}$$

A state-space representation, like the one given by (1-2) in our simple example, is obtained here by defining:

$$X_t = \begin{bmatrix} x_{t-1} \\ \vdots \\ x_{t-p_x} \\ s_t \\ \vdots \\ s_{t-p_s} \end{bmatrix}$$

While the dimension of X_t in our example was equal to two, the size of X_t is in general equal to $r = mp_x + q(p_s + 1)$, where $p_x = max(p_{\Lambda_1}, p_c)$ and $p_s = max(p_{\Lambda_2, p_d})$. The parameter r, determines the complexity in the propagation mechanism of the shocks, determining the "static rank", as defined by Giannone et al. (2006). When r and q are smaller than the number of observables, as in our prototypical RBC economy, one can say that the model has *reduced* static and dynamic rank.

Both the static rank r and the dynamic rank q represent testable restrictions of a model economy, and help to build a bridge between the general equilibrium theories and the class of dynamic factor models (see Forni et al. (2007) for further details). Beyond these restrictions, the behavioural constraints embedded in the economic model help achieve further parsimony. Although our simple model has $r = 2$ and $q = 1$, alternative formulations with larger static rank r are consistent with more complex propagation mechanisms. For example, in Altug's model

(1989) with a time-to-build feature, the static rank depends on the number of quarters that investment projects require in order to become capital.

Figure () provides an overview of the whole set of models considered.

3 Evaluating the fit of RBC, DFM and VARs: An Out-of-Sample Perspective

Our focus on out-of-sample forecasting is mainly motivated by the need for a robust measure of the alternative models' goodness of fit. Out-of-sample measures of forecast accuracy overcome the curse of in-sample overfitting[7].

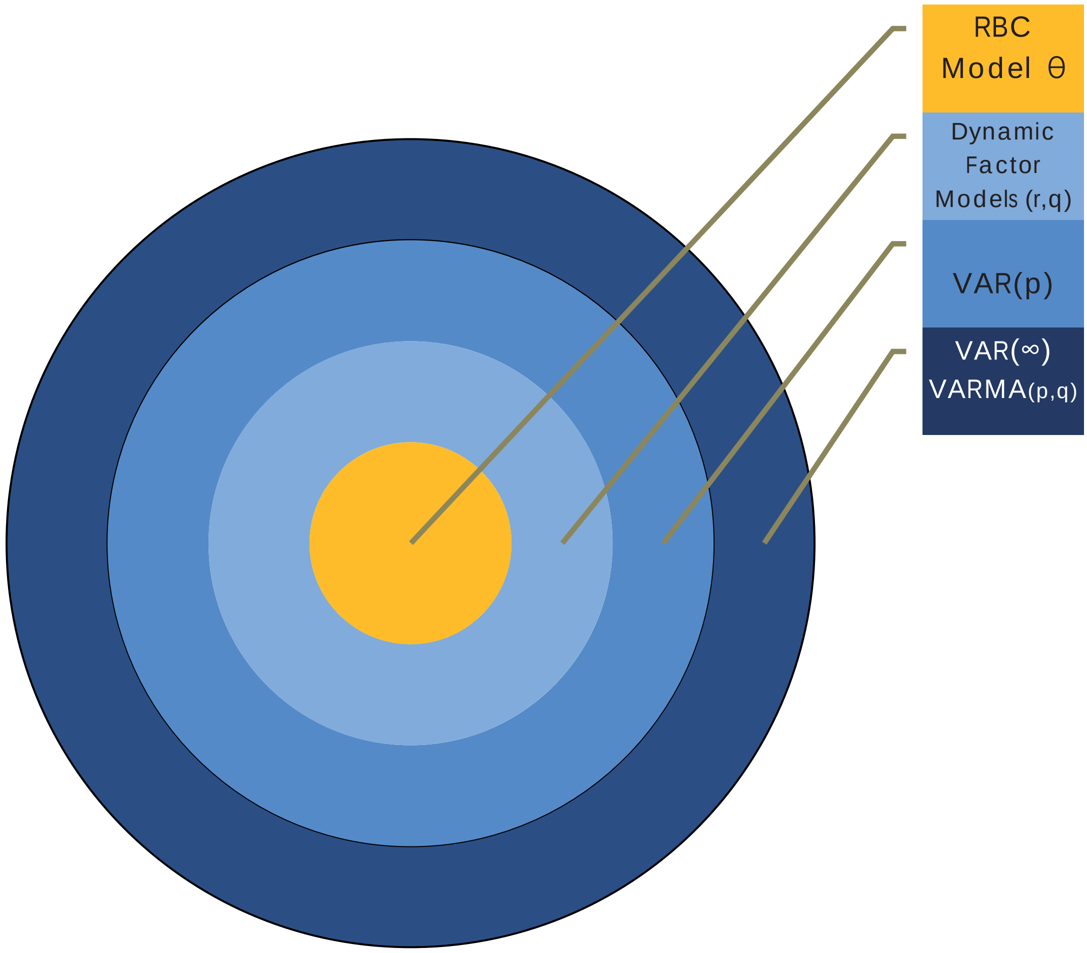
The main explanation for why RBC models may provide forecast accuracy gains can be found implicitly in Beveridge and Nelson's definition of the cycle (1981). If business cycles are in essence defined as predictable deviations of the data from the mean rate of drift or balanced growth path, RBC models that generate cycles in the sense of Beveridge-Nelson may contribute to forecasting. After a technological "surprise", agents gradually readjust their consumption, saving and hours worked, resulting in predictable (co)movements in these time series. From a statistical point of view, the reason why RBC models may contribute to forecasting is related with their parsimony. It is well known that parsimony is an advantageous feature in forecasting practice, due to the efficiency gains resulting from estimation of a small number of parameters[8].

On the contrary, the literature contains arguments on how difficult it is for the RBC models to provide propagation mechanisms that are sufficiently strong to account for predictable variations in the observed data. Rotemberg and Woodford

[7] Hansen (2009), for example, provides a statistical framework where in-sample fit is inversely proportional to out-of-sample accuracy. That is, good in-sample fit can easily translate into poor out-of-sample forecasts

[8] A wide discussion is provided in Chapter 12 of Clemens and Hendry (1998).

Figure 1: Exploring the Parametric Space



Broadly speaking a given dynamic factor model is always encompased in a VAR(p), with a suitable choice of p. At the same time, an RBC model is encompased in a dynamic factor model defined by a suitable choice of r, q. Thus, for any given RBC model, there exists a dynamic factor model and a VAR that encompases it.

(1996) persuasively argue that forecastable[9] output fluctuations in a prototypical calibrated RBC model have much lower variance than that resulting from VAR projections. This confirms the large discrepancy between calibrated models and the observed data found by Watson (1993) and by Cogley and Nason (1995).

This stream of evidence, however, leaves room for a revisit of the forecasting ability of RBC models. First of all, the comparison between a calibrated RBC model and a VAR is unfair. This was initially acknowledged by Kydland and Prescott (1989). They argued that given the *measurement problems* and the abstract nature of the RBC model, when it is tested against the VAR the data is likely to reject it. Moreover, the calibration approach is traditionally intended to match the means, variances and low orders of correlation found in the data, while estimated VARs have enough potential to approximate the full autocorrelation structure of the data and ensure a superior in-sample fit. A second argument for revisiting the issue is that none of the critiques mentioned above base their conclusions on out-of-sample forecasting experiments where the large number of parameters in the VAR could reduce forecast accuracy, shifting the balance in favour of RBCs. The successful out-of-sample exercises conducted by Ireland (2004) or Ingram and Whiteman (1994) are consistent with this idea.

The following subsections will help us understand the extent to which dynamic factor models can improve forecast accuracy when they incorporate the static and dynamic rank reduction restrictions typical of simple RBC models. Beyond these useful rank reduction constraints, RBC models' behavioural assumptions determine tight cross-equation restrictions that, as we show in our application, do not significantly assist forecast accuracy.

[9]In their paper, the term *forecast* or *prediction* always refers to an *in-sample* projection.

3.1 A Forecasting Competition

Following Sargent (1989), we conduct maximum likelihood estimation of the RBC model parameters under the assumption that the observed data contains serially correlated measurement errors that are independent across variables (idiosyncratic) and independent of the RBC economy[10].

Regarding the class of dynamic factor models, estimation will be conducted with the same method and identical assumptions regarding the measurement errors. In the appendix, we compare the RBC model estimation results with those of a less restrictive dynamic factor model specification that shares the same static and dynamic rank reduction restrictions.

We will estimate all the models using this measure of output, consumption and hours worked. In order to forecast investment are recovered from the output and consumption projections. While we acknowledge that the data might be just a noisy estimate of the actual concepts used in the model, we do not intend to use additional information to enhance estimation as is done in the literature on *large* dynamic factor models.

Data and Design of the Forecasting Exercise:

The data[11] used is expressed in per-capita terms using the civilian, non-institutional population, age 16 and over. Hours worked are measured by hours of wage and salary earners on private, non-farm payrolls. Consumption is real personal consumption expenditure and investment is real gross private domestic investment. Finally output is calculated as the sum of consumption and investment.

The forecasts to be constructed aim to match the log-levels of output, con-

[10] Many authors have followed the same approach, for example, Hall (1996), McGrattan,Rogerson and Wright (1997) or Ireland (2001).

[11] The hours worked series is taken from the Bureau of Labor Statistics' Establishment Survey. All other series come from the Federal Reserve Bank of St. Louis FRED database.

sumption, investment and hours worked, and the Root Mean Squared errors will be constructed accordingly. The estimation sample and the evaluation period is the same as in Ireland (2004), so that our results are perfectly comparable. Thus, our models are recursively estimated with data ranging from 1948Q1 to 2002Q1. The evaluation sample is 1985Q1 − 2002 Q2.

Finally, the forecast accuracy results reported for each model will be constructed in two different ways: first, by estimating the model parameters with the information set available (*recursive* estimation window or *expanding* estimation window); and second, by estimating the model parameters with the last 148 data points or quarters available at the time of the forecast (*fixed* estimation window).

3.2 Our Simple RBC Model at Forecasting

Ireland (2004) showed that the out-of-sample forecasting performance of our prototypical RBC model, augmented with a vector of measurement errors[12], is surprisingly good. Table 1 displays the Square Rooted Mean Squared Errors (SRMSE) of our benchmark out-of-sample forecasting exercise, which is based on a recursive estimation of the RBC model. The evaluation sample goes from 1985 Q1 to 2002 Q2 so that our results coincide exactly with Ireland (2004)'s. The results, however, are only informative when compared with a set of competing models.

Before starting the analysis, it is useful to understand whether the recursive estimation scheme is very different from a fixed window estimation strategy. In addition, since the variance of the measurement error for output does not seem to be highly significant, we conduct the same exercise under the assumption that there is not a measurement error in output[13].

[12] In his article, the measurement error has a VAR form. In this paper, we focus on the particular case of variable specific noise.

[13] Since output is defined in the model as the sum of consumption and investment, arguing

As shown in the left-hand panel of Table 2, taking measurement error out of output makes practically no change to the results. By comparing the right-hand and left-hand panels we see that the fixed window estimation is only slightly better at forecasting hours worked, although the improvement, a 4% reduction in SRMSE at all horizons, is not significant. All the forecasting exercises performed in this section will be conducted with both estimation strategies to ensure the robustness of our results.

Table 1: SRMSE of the RBC Model (**Benchmark**)

Recursive estimation or *expanding window* [1948Q1 to 1985Q2-h]→[1948Q1 to 2002Q2-h]				
Log Likelihood	-2193.5			
Number of Parameters	12			
static rank (r)	2			
dynamic rank (q)	1			
noise shocks	3			
horizon	Y	C	I	H
h=1	0.70	0.49	3.22	0.57
h=2	1.23	0.74	4.96	1.09
h=3	1.72	0.97	6.55	1.60
h=4	2.18	1.25	8.01	2.08

*Evaluation sample: 1985 Q1 to 2002 Q2

3.3 The Importance of Rank-Reduction Restrictions

This exercise complements the evidence offered by Ireland (2004) and by Ingram and Whiteman (1994) on the forecasting ability of RBC models. As opposed to these authors, we go beyond the comparison with models in the VAR class in order to understand the RBC model's goodness of fit and the usefulness of

that output is not subject to measurement errors while its components are is only a convenient simplification.

Table 2: *Relative* SRMSE of RBC Model with $\sigma_y = 0$

SRMSE relative to **Benchmark**

recursive estimation	**rolling** window
[1948Q1 to 1985Q2-h]	[1948Q2-h to 1985Q2-h]
→[1948Q1 to 2002Q2-h]	→ [1965Q2-h to 2002Q2-h]

RBC MODEL assuming $\sigma_y = 0$

r	2							2	r
q	1	L.	-2192.0		-1540.6		L.	1	q
noise shocks	2	n.p.	10		10		n.p.	2	noise shocks
horizon	Y	C	I	H	Y	C	I	H	horizon
h=1	1.00	0.99	0.98	1.00	0.99	0.99	0.98	0.96	h=1
h=2	1.00	0.98	0.96	1.00	1.00	0.98	0.96	0.96	h=2
h=3	1.00	0.97	0.95	1.00	1.00	0.97	0.94	0.96	h=3
h=4	1.00	0.99	0.94	1.00	1.00	0.99	0.94	0.96	h=4

*Evaluation sample: 1985 Q1 to 2002 Q2. The *Relative* SRMSE is the ratio of the actual SRMSE and the Benchmark SRMSE. Thus, a model with a ratio equal to 0.94 is able to correct 6 % of the benchmark forecast error (in terms of SRMSE).

Table 3: *Relative* SRMSE of the class of Dynamic Factor Models

recursive estimation	**rolling** window
[1948Q1 to 1985Q2-h]	[1948Q2-h to 1985Q2-h]
→[1948Q1 to 2002Q2-h]	→ [1965Q2-h to 2002Q2-h]

DYNAMIC FACTORS MODELS (reduced static and/or dynamic rank)

r	1							1	*r*
q	1	L.	-2219.2		-1540.6		L.	1	*q*
noise shocks	3	n.p.	10		10		n.p.	3	noise shocks
horizon	Y	C	I	H	Y	C	I	H	horizon
h=1	1.01	1.06	0.98	0.94	1.01	1.04	0.98	0.91	h=1
h=2	0.99	1.09	0.96	0.94	0.99	1.05	0.94	0.90	h=2
h=3	0.98	1.09	0.94	0.94	0.97	1.05	0.92	0.90	h=3
h=4	0.96	1.07	0.93	0.93	0.95	1.04	0.91	0.90	h=4

r	2							2	*r*
q	1	L.	-2251		-1602.5		L.	1	*q*
noise shocks	3	n.p.	17		15		n.p.	2	noise shocks
horizon	Y	C	I	H	Y	C	I	H	horizon
h=1	0.88	1.03	0.88	0.61	0.87	1.00	0.87	0.59	h=1
h=2	0.90	1.08	0.85	0.57	0.89	1.02	0.85	0.58	h=2
h=3	0.93	1.11	0.86	0.57	0.91	1.03	0.86	0.58	h=3
h=4	0.95	1.13	0.87	0.58	0.92	1.05	0.86	0.60	h=4

r	2							2	*r*
q	2	L.	-2292.8		-1583.2		L.	2	*q*
noise shocks	3	n.p.	17		15		n.p.	2	noise shocks
horizon	Y	C	I	H	Y	C	I	H	horizon
h=1	0.88	1.03	0.88	0.61	0.87	1.00	0.87	0.59	h=1
h=2	0.90	1.08	0.85	0.57	0.89	1.02	0.85	0.58	h=2
h=3	0.93	1.11	0.86	0.57	0.91	1.03	0.86	0.58	h=3
h=4	0.95	1.13	0.87	0.58	0.92	1.05	0.86	0.60	h=4

r	3							3	static rank
q	1	L.	-2297.7		-1612.7		L.	1	*r*
noise shocks	2	n.p.	22		22		n.p.	2	*q*
horizon	Y	C	I	H	Y	C	I	H	horizon
h=1	0.85	1.04	0.87	0.59	0.83	1.03	0.84	0.59	h=1
h=2	0.89	1.09	0.84	0.57	0.86	1.04	0.82	0.59	h=2
h=3	0.93	1.12	0.87	0.57	0.89	1.03	0.85	0.60	h=3
h=4	0.94	1.15	0.87	0.58	0.90	1.06	0.85	0.60	h=4

r	3							3	*r*
q	2	L.	-2242.7		-1620.6		L.	2	*q*
noise shocks	2	n.p.	22		22		n.p.	2	noise shocks
horizon	Y	C	I	H	Y	C	I	H	horizon
h=1	1.26	1.57	0.93	0.62	1.08	1.07	1.01	0.82	h=1
h=2	1.38	1.88	0.95	0.67	1.08	1.16	0.98	0.83	h=2
h=3	1.43	2.04	0.97	0.74	1.12	1.23	1.01	0.86	h=3
h=4	1.43	2.00	0.98	0.79	1.14	1.24	1.04	0.89	h=4

VECTOR AUTOREGRESSIVE MODEL

VAR(4)

horizon	Y	C	I	H	Y	C	I	H	horizon
h=1	0.95	1.08	0.87	0.58	0.94	1.01	0.89	0.62	h=1
h=2	1.30	1.28	1.21	0.99	1.28	1.21	1.21	1.03	h=2
h=3	1.42	1.51	1.30	1.18	1.35	1.40	1.26	1.17	h=3
h=4	1.43	1.50	1.31	1.27	1.34	1.36	1.26	1.23	h=4

*Evaluation sample: 1985 Q1 to 2002 Q2. The *Relative* SRMSE is the ratio of the actual SRMSE and the Benchmark SRMSE (RBC). Thus, a model with a ratio equal to 0.94 is able to correct on average a 6 % of the benchmark (RBC) forecast error.

NB: The RBC model considers the data in deviations from a balanced growth path given by the estimated linear trend, that is, labour-augmenting technological progress. In order to ensure that differences in forecast accuracy are not due to differences in the estimation of trend of the competing models, we will set the trend of all the Dynamic Factor Models and VARs at the values obtained in the stepwise estimation of the RBC model evaluated in Table 1.

its restrictions. Accordingly, we consider the set of **dynamic factor models** (DFMs), which also incorporate restrictions on the number of states r, and on the number of shocks q driving the states. Models of this type are defined by equations (9-10).

Table 3 depicts the SRMSE of the alternative models with restrictions in q and r divided by those corresponding to the Benchmark RBC model evaluated in Table 1. Thus, this ratio will be less than one for the models whose forecasts are more accurate than those produced by the RBC model.

Forecast Evaluation:

First, the simplest DFM specification evaluated in Table 3 has static rank r equal to one, and dynamic rank q equal to 1. This model represents no significantly improvement on the performance of the RBC model.

The second model is a DFM specification with the same rank reduction restrictions as the RBC model. It has two static factors, $r = 2$, that are driven by a single shock, $q = 1$. The left-hand side of this table corresponds to a recursive estimation scheme where the sample size increases, while the right-hand side is based on a fixed estimation window. In both cases, the SRMSE gains with respect to the RBC model are significant at all horizons for output, investment and hours, but not for consumption. Overall, the set of constraints implied by the RBC model that go beyond the rank-reduction restrictions do not seem to be useful for forecasting. The gains of the consumption smoothing behaviour of the RBC model seem to render the consumption forecast errors less volatile, although the gains in terms of SRMSE are less than to 20% in all cases.

The next model has the same static rank $r = 2$. Introducing an additional common shock in the state equation, $q = 2$, yields exactly the same results; in this case, the maximum likelihood solution attributes most of the variance to one of the shocks, while the second shock is practically zero.

By contrast, the DFM specification where the single common shock assumption is maintained, $q = 1$, but the number of static factors is increased to three, $r = 3$, represents no significant improvement on the previous specification with $r = 2$ and $q = 1$. This leads us to believe that although $r = 2$ is enough to capture the propagation of a single shock on output, consumption, investment and hours, the data are able to identify one additional static factor.

However, the next DFM specification shown in the table, also with $r = 3$, but now with $q = 2$, is not competitive at forecasting, meaning that the data we are using in the estimation are unable to successfully identify more complex propagation mechanisms for two shocks.

Finally, the most unrestricted specification included in Table 3 is a VAR of order four. This model produces better forecasts for hours worked than the RBC model only in the very short run (1 step ahead), correcting 40% of the RBC model's SRMSE. For the remaining variables, the accuracy one quarter ahead is comparable for the two models, but the RBC model outperforms the VAR at forecasting two quarters ahead and beyond for all variables. The ability of this simple general equilibrium model to compete with models belonging to the VAR class is surprising, given the common wisdom in the literature that RBC models have serious difficulties generating predictable fluctuations that explain the variance of the macro time series (see, for example, Rotemberg and Woodford (1996), or Cogley and Nason (1995)).

All these results help us conclude that the dynamic rank reduction restrictions ($q = 1, r = 2$) embedded in the RBC model are *sufficient* to provide forecast accuracy gains over the simple RBC model, which also incorporates behavioural restrictions in the form of tight cross-equation restrictions derived from the general equilibrium environment. The inability of the RBC model, which is also characterised by $r = 2, q = 1$, to compete with the dynamic factor model allows us to claim that the "behavioural" assumptions of the theory are not supported by the data. However, it is fair to admit, that none of the competing models improve on the RBC model's performance at forecasting consumption.

To conclude, we are aware that the restrictions in r and q, which apply both to the RBC model and the dynamic factor models, may not be the only source of forecast accuracy. By taking measurement errors into account, the business cycle co-movements are separated from idiosyncratic dynamics, leading to a less restrictive representation of the data.

The following subsection focuses on the robustness of these results, incorporating a larger number of models in our forecasting competition.

4 Robustness: Model Confidence Sets

The empirical results point to the improved forecasting performance of a particular class of models that incorporate restrictions in the second-order moments of the data. Notably, these restrictions imply a reduction in the number of factors to less than or equal to the number of observables in our application. Also the number of shocks is constrained to be less or equal to the number of factors. The question now is whether our conclusions are robust. Do the dynamic and static rank reduction properties of the RBC model "significantly" achieve higher forecast accuracy[14] than the overall set of behavioural constraints that arise from the "micro foundations"?

Hansen, Lunde and Nason (2005) offer a very suitable framework to actually test whether a particular class of models contains the subset of best forecasting models: Model Confidence Sets for Forecasting Models (MCSs). The MCS testing approach confirms our conjecture from the SRMSE results, that is, the class of dynamic factor models with dynamic and static rank reduction contains the best forecasting models. The MCS is analogous to a confidence interval for a

[14] Since we are comparing encompassing models, we will compare the forecasts produced with the fixed window estimation scheme alone. Otherwise, the stationary assumption on the forecasting errors would be violated as an increasing number of data points are used to estimate the different models.

parameters; the purpose of this approach is to use the sample information (e.g. SRMSE) to select the set of most successful models with the guarantee that this set contains the **best model(s)** with a pre-specified probability (significance level of the test). Table 4 ranks the models (from worst to best) according to their performance (SRMSE) at forecasting output, consumption, investment and hours worked at different horizons. The p-value next to each model is **not** the probability that a particular model is the best model, for the same reason that p-values in classical inference are not the probability of a particular hypothesis being true.

The p-values are related to each sequential EPA (Equal Predictive Accuracy) test. The first EPA test is on the whole set of models at a confidence level α. If the test rejects the null hypothesis (p-value$< \alpha$) of equal predictive accuracy, then an elimination rule is applied to discard the worse performing model. The test is then applied to the surviving models again and again, always keeping α. The testing procedure ends as soon as the null of EPA is not rejected (p-value$>$ α). If the test fails to reject the null at the very beginning, it means that the data is not sufficiently informative about which is the best model and that none of them is significantly better than the rest. This actually happens in our empirical application when the MCS test is applied to the one quarter ahead consumption forecasts. The RBC model proved to have the smallest SRMSE, but one cannot reject the hypothesis of equal forecast accuracy applied to the whole set of models.

Our Model Confidence Set

By fixing the significance level of the test to 10%, we are able to select (see Tables 4 and 5) the smallest model set that contains the **best model(s)** with a probability equal or larger than 90 %. The RBC model forecasts belong to the Model Confidence Set (MCS) only in the case of output (four quarters ahead) and consumption at all horizons.

Only models belonging to the DFM class are selected in all sixteen MCS (4

Table 4: Model Confidence Sets

Level α= 10% MCS

OUTPUT							
horizon=1		horizon=2		horizon=3		horizon=4	
model set	p-value	model set	p-value	model set	p-value	model set	p-value
VAR(1)	0.001	VAR(1)	0.001	VAR(3)	0.000	VAR(2)	0.000
q=2 r=3	0.005	VAR(2)	0.001	VAR(1)	0.000	VAR(3)	0.000
q=1 r=1	0.024	VAR(3)	0.002	VAR(2)	0.001	VAR(4)	0.000
AR(1)	0.024	VAR(4)	0.005	VAR(4)	0.002	VAR(1)	0.001
RBC	0.024	q=2 r=3	0.010	q=2 r=3	0.008	q=2 r=3	0.009
VAR(4)	0.131	q=1 r=1	0.032	AR(1)	0.055	AR(1)	0.091
VAR(3)	0.178	RBC	0.032	q=1 r=1	0.055	RBC	0.126
q=$\{1,2\}$ r=2	**0.238**	AR(1)	0.032	RBC	0.099	q=1 r=1	0.186
q=1 r=3	**0.302**	**q=$\{1,2\}$ r=2**	**0.489**	**q=$\{1,2\}$ r=2**	**0.493**	**q=$\{1,2\}$ r=2**	0.436
VAR(2)	1.000	**q=1 r=3**	**1.000**	**q=1 r=2**	**1.000**	**q=1 r=3**	**1.000**

CONSUMPTION							
horizon=1		horizon=2		horizon=3		horizon=4	
model set	p-value	model set	p-value	model set	p-value	model set	p-value
q=2 r=3	0.630	VAR(1)	0.041	VAR(3)	0.001	VAR(1)	0.007
VAR(1)	0.719	VAR(2)	0.066	VAR(1)	0.001	VAR(3)	0.008
AR(1)	0.743	VAR(3)	0.085	VAR(2)	0.002	VAR(4)	0.011
q=1 r=3	**0.779**	q=2 r=3	0.117	VAR(4)	0.010	VAR(2)	0.024
VAR(3)	0.779	VAR(4)	0.215	q=2 r=3	0.065	*q=2 r=3*	0.114
q=1 r=1	0.779	AR(1)	0.595	AR(1)	0.771	**q=1 r=3**	**0.801**
q=$\{1,2\}$ r=2	**0.903**	q=1 r=1	0.626	**q=1 r=3**	**0.794**	q=1 r=1	0.801
VAR(4)	0.903	**q=$\{1,2\}$ r=2**	**0.626**	q=1 r=1	0.794	**q=$\{1,2\}$ r=2**	**0.801**
VAR(2)	0.903	**q=1 r=3**	**0.595**	**q=$\{1,2\}$ r=2**	**0.794**	AR(1)	0.801
RBC	1.000	RBC	1.000	RBC	1.000	RBC	1.000

Evaluation sample: 1985 Q1 to 2002 Q2. The Model Confidence Sets capture for each variable and each projection horizon the set of best forecasting models (according to the SRMSE).

Table 5: Model Confidence Sets

Level α= 10% MCS

INVESTMENT

horizon=1 model set	p-value	horizon=2 model set	p-value	horizon=3 model set	p-value	horizon=4 model set	p-value
VAR(1)	0.001	VAR(1)	0.001	VAR(4)	0.003	VAR(4)	0.001
q=1 r=1	0.003	q=1 r=1	0.002	VAR(3)	0.003	VAR(3)	0.001
RBC	0.004	RBC	0.002	VAR(2)	0.003	VAR(2)	0.001
AR(1)	0.012	AR(1)	0.002	VAR(1)	0.003	VAR(1)	0.001
q=2 r=3	0.050	VAR(4)	0.002	q=2 r=3	0.015	q=2 r=3	0.007
q=1 r=3	**0.486**	VAR(3)	0.002	RBC	0.032	RBC	0.023
q={1,2} r=2	**0.486**	VAR(2)	0.002	q=1 r=1	0.053	q=1 r=1	0.050
VAR(4)	0.486	q=2 r=3	0.009	AR(1)	0.053	AR(1)	0.050
VAR(3)	0.486	**q=1 r=3**	**0.266**	**q=1 r=3**	**0.411**	**q=1 r=3**	**0.322**
VAR(2)	1.000	**q={1,2} r=2**	**1.000**	**q={1,2} r=2**	**1.000**	**q={1,2} r=2**	**1.000**

HOURS WORKED

horizon=1 model set	p-value	horizon=2 model set	p-value	horizon=3 model set	p-value	horizon=4 model set	p-value
q=1 r=1	0.000	q=1 r=1	0.000	RBC	0.000	q=1 r=1	0.000
RBC	0.000	RBC	0.000	VAR(3)	0.000	RBC	0.000
AR(1)	0.000	AR(1)	0.000	VAR(2)	0.000	VAR(4)	0.000
VAR(1)	0.000	VAR(4)	0.000	VAR(1)	0.000	VAR(3)	0.000
q=2 r=3	0.001	VAR(3)	0.000	q=1 r=1	0.000	VAR(2)	0.000
VAR(4)	0.115	VAR(2)	0.000	AR(1)	0.000	VAR(1)	0.000
q=1 r=3	**0.253**	VAR(1)	0.000	VAR(4)	0.000	AR(1)	0.000
q={1,2} r=2	**0.253**	q=2 r=3	0.006	q=2 r=3	0.005	q=2 r=3	0.000
VAR(3)	0.253	**q=1 r=3**	**0.335**	**q=1 r=3**	**0.411**	**q=1 r=3**	**0.877**
VAR(2)	1.000	**q={1,2} r=2**	**1.000**	**q={1,2} r=2**	**1.000**	**q={1,2} r=2**	**1.000**

Evaluation sample: 1985 Q1 to 2002 Q2. The Model Confidence Sets capture for each variable and each projection horizon the set of best forecasting models (according to the SRMSE).

variables $\times$ 4 horizons). In particular, the forecast accuracy gains of the dynamic factor model that is closest to the RBC model in terms of static and dynamic rank ($r = 2$ and $q = 1$) are confirmed to be significant. As discussed earlier, adding a second shock, $q = 2$, give exactly the same forecasting result; this is because the additional shock is estimated to have a very small variance. Both specifications appear in the table as $q = \{1, 2\}, r = 2$ in a single cell. Therefore, we can argue that the failure of the RBC model cannot be a result of the rank reduction restrictions.

While simple models are likely to perform well at forecasting, a more naive dynamic factor model with $r = 1$ is never selected. This implies that more complex dynamics are required to capture basic macroeconomic co-movements. Conversely, the dynamic factor model with $r = 3$ and $q = 2$, which has the potential to capture more sophisticated propagation mechanisms for two structural shocks, does not survive our forecasting test.

Another parsimonious representation is given by a VAR(p) with $p = 1$, which can be derived from the RBC model under the assumption that there are no measurement errors (see Section 2.2.). Such a model is never preferred over the competing models. Alternatively, VAR(p) specifications with $p > 1$ only belong to the MCS in the very short run, in line with the common wisdom that purely statistical models perform reasonably well in the short term.

The question of what is driving the competitive advantage of the RBC and DFM specifications over the VAR models is not answered here, since our focus is on the RBC alone, and its properties. The explicit consideration of measurement errors by both the RBC and the DFM models could be an important factor, complementing the parsimony provided by the rank reduction restrictions.

5 Conclusions

This paper acknowledges that the restrictions implied by DSGE models provide a parsimonious representation of the data that may be used in out-of-sample forecasting. The contribution is to disentangle the different types of restrictions that are characteristic of models of this type. Along the lines of Giannone et al. (2006), we use the state-space parameterisation of the factor models proposed by Forni et al. (2007) to understand whether the strict behavioural assumptions implied by a DSGE model provide forecast accuracy gains beyond those given by the weak statistical restrictions of the DSGE model (dynamic and static rank).

The forecast evaluation conducted in this paper allows us to conclude that weak statistical restrictions embedded in a simple RBC model, well known to economists, provide us with valuable information that can be used to generate good forecasts. Conversely, the behavioural constraints embedded in the RBC model do not assist at forecasting.

The focus on forecasting helps provide a robust characterisation of the models' ability to fit the data, preventing misleading comparisons with models that are only capable of *learning by heart* the sample information (over-fitting). Our results help reconcile the out-of-sample findings obtained by Ireland (2004) and by Ingram and Whiteman (1994), in favour of RBC models, with the more critical in-sample type of results obtained by Rotemberg and Woodford (1996), Cogley and Nason (1995) or Watson (1993). Along the same lines as the findings of the latter authors, our results suggest that the *overall* set of restrictions embedded in the RBC model is rejected by the data. In turn, empirical support for the RBC model is found when we isolate the forecast accuracy resulting from the restrictions in the second-order moments of the data (i.e. restrictions in the *dynamic* and *static* ranks).

The first papers acknowledging that the state-space representation of an RBC model, augmented with idiosyncratic measurement error components, has a dynamic factor analytical form were Altug (1989) and Sargent (1989). Our exercise differs from Altug's in the out-of-sample nature of the validation experiment and in the parametrisation of the dynamic factor models. Drawing on Giannone et al. (2006), we impose restrictions not only on the number of shocks (dynamic rank), but also in the simplicity of their propagation mechanism (static rank).

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A Estimation results: Comparing the RBC model with the dynamic factor model with $r = 2$ and $q = 1$

We acknowledge that neither the RBC model nor the common component of the dynamic factor representations can explain all the possible variances present in the data. Their aim is to account for the observed co-movements through the common shocks that affect all the variables. Some empirical evidence on the presence of noise can be found in Fixler and Nalewaik (2007), where the reliability of GDP (Gross Domestic Product) and GDI (Gross Domestic Income) as alternative measurements of economic activity is discussed. In its report of 12/01/08, the NBER Business Cycle Dating Committee shares this view, acknowledging that output measurement from the product and income side proceed somewhat independently.

In this section we explain the main identification issues relating to the dynamic factor models and the RBC model that take noise explicitly into account. Moreover, the estimation results corresponding to the RBC model will be compared with those resulting from the dynamic factor model specification that shares its static and dynamic rank restrictions ($r = 2$, $q = 2$).

A.1 Identification

Table 6 shows the maximum likelihood estimates of the system (1-2) augmented with measurement error. That is:

$$\begin{aligned} \mathrm{Y_t} &= \Lambda_{3\times 2}(\vartheta)\mathrm{X_t} + \overbrace{\xi_t}^{measuement\ error} \\ \mathrm{X_t} &= \Phi_{2\times 2}(\vartheta)\mathrm{X_{t-1}} + B(\vartheta)\epsilon_t \end{aligned}$$

where the measurement errors are autocorrelated, i.e. $\xi_{i,t} = \Psi_i \xi_{i,t} + v_{i,t}$ for

Table 6: RBC estimated parameters

RBC model (or $DFM(\vartheta)$)					
Parameter	ML Estimate	SE	Parameter	ML Estimate	SE
β	0.990	0	Ψ_y	1.000	(0.00005)
θ	0.471	(0.060)	Ψ_c	0.866	(0.078)
δ	0.025	0	Ψ_h	0.995	(0.006)
η	1.005	(0.001)	σ_y	0.002	(0.0006)
γ	0.004	(0.000)	σ_c	0.006	(0.0003)
A	1.438	(0.492)	σ_h	0.007	(0.0004)
ρ_a	0.999	(0.001)	σ_a	0.009	(0.0006)

$i = y, c, h$. In order to achieve identification, these errors are assumed to be uncorrelated across variables and uncorrelated with the technology shock ϵ_t. This assumption is equivalent to the orthogonality between idiosyncratic and common components in the literature on factor models.

The parameters that appear in the table with standard error equal to zero have been fixed. All details on the implementation of this maximum likelihood (ML) procedure (and Matlab codes) can be found in the Ireland's Technical Appendix (2004).

As is clear from the notation used, there is a mapping from the RBC parameters ϑ to the matrices of coefficients of our state-space representation.

$$\vartheta \overset{non-linear\ mapping}{\longrightarrow} \Lambda, \Phi, B$$

Therefore, the parameter estimates of Table 6 can be written in terms of the coefficients of the state-space form of the system. The left-hand side of Table 7 illustrates this point. The Hessian evaluated at the ML values in Table 6 is used to determine the standard errors for the dynamic factor model parameters. Note that null standard error in one of the parameters associated to the state-equation signals that its value is directly given from Table 6 with no uncertainty.

The right-hand side of Table 7 shows the ML estimation results of a Dynamic Factor Model defined by equations 9 and 10, with a similar parametrisation to the RBC model ($q = 1$ and $r = 2$), but free from the additional economic restrictions, i.e. no dependence on ϑ:

$$\mathrm{Y_t} = A_{3\times}\mathrm{f_t} + \overbrace{\xi_t}^{measuement\ error} \tag{11}$$

$$\mathrm{f_t} = D_{2\times 2}\mathrm{f_{t-1}} + \underbrace{R\epsilon_t^f}_{u_t} \tag{12}$$

Here, f_t represents a vector of atheoretical *factors* rather than state variables of the RBC model. The measurement errors ξ_t may be autocorrelated, i.e. $\xi_{i,t} = \Psi_i \xi_{i,t} + v_{i,t}$ for $i = y, c, h$. In order to distinguish the *noise* from *structure*, it is assumed, first, that the noise is idiosyncratic or variable-specific. This rules out cross-correlation in ξ_t, and absence of correlation with the structural shock ϵ_t^f, which is common to all variables.

Nevertheless, two additional assumptions are required to identify the factors. First, we need to assume that the covariance of $R\epsilon_t^f = [\mathrm{f_t} - D_{2\times 2}\mathrm{f_{t-1}}]$ is given, for example, by the RBC model.

Without this normalisation, the following system would be observationally equivalent:

$$\begin{aligned} \mathrm{Y_t} &= \Lambda_{3\times 2} G^{-1}\mathrm{g_t} + \xi_t \\ \mathrm{g_t} &= G\Phi_{2\times 2} G^{-1}\mathrm{g_{t-1}} + Gu_t \end{aligned}$$

where G is an arbitrary invertible $r \times r$ matrix, and $g_t = G\mathrm{f_t}$. Therefore, our normalisation strategy assumes that $cov(R\epsilon_t^r) = cov(B(\vartheta)\epsilon_t)$. It is customary to normalise the series before estimation in the literature on dynamic factor models.

A second identification assumption is required, since there are orthonormal matrices that can rotate the static factors without affecting our normalisation assumption above. That is, a matrix Ω such that $\Omega'\Omega = I$ could be used to define a new observationally equivalent representation of our system:

$$\begin{aligned} \mathrm{Y_t} &= \Lambda_{3\times 2}\Omega^{-1}\mathrm{h_t} + \xi_t \\ \mathrm{h_t} &= \Omega\Phi_{2\times 2}\Omega^{-1}\mathrm{h_{t-1}} + \Omega u_t \end{aligned}$$

where $h_t = \Omega f_t$. In order to solve this identification problem, we set the matrix R in equation 12 at the value of $B(\vartheta)$, which is determined by the solution of the RBC model, in equation 2. This identification strategy is in spirit equivalent to the one followed in structural VAR analysis.

The estimates of the factor loadings Λ_{ij} are very different in the two models, as shown in Table 7. Notably, in the RBC model (DFM(ϑ)), the estimate of the standard deviation of the noise component in output, σ_y, is very small, but still significantly different from zero, while in the DFM specification this variance is not significantly different from zero. Moreover, the autocorrelation coefficient of this measurement shock (Ψ_y) cannot be estimated very precisely. These observations have led us to perform some of the forecasting exercises ignoring the presence of measurement error for output.

A.2 Forecast Error Variance Decomposition

The forecast error variance decomposition provides useful information on the role of the structural shock in each model. Overall, the variance decomposition implied by both the RBC model (upper part of Table 8) and the dynamic factor specification (lower part) is very similar, reflecting the presence of a common shock that accounts for a very large proportion of the variance of the forecast errors. There are, however, significant differences across the variables.

As shown in Table 8, the common shock of both the RBC model and the DFM specification explain most of the output variance at all horizons, leaving no explanatory role for measurement error. The same result holds for investment, where the common shock accounts for most of the variance at all horizons.

Table 7: Estimation Results

$DFM(\vartheta)$ Log Likelihood = 2193			DFM Log Likelihood = 2251		
State Equation (factor dynamics)					
Parameter	ML Estimate	SE	Parameter	ML Estimate	SE
$\Theta_{11}(\vartheta)$	0.957	0.013	D_{11}	0.412	0.091
$\Theta_{12}(\vartheta)$	0.082	0.014	D_{12}	25.011	1.003
$\Theta_{21}(\vartheta)$	0	0	D_{21}	-0.008	0.003
$\Theta_{22}(\vartheta)$	0.999	0.001	D_{22}	1.273	0.066
$\sigma_a(\vartheta)$	0.009	0.001	σ_a	0.009	0
Measurement Equation (factor loadings and measurement error dynamics)					
Parameter	ML Estimate	SE	Parameter	ML Estimate	SE
Ψ_y	1.000	0.00005	Ψ_y	-0.426	0.371
Ψ_c	0.866	0.076	Ψ_c	0.965	0.017
Ψ_h	0.995	0.006	Ψ_h	0.996	0.004
σ_y	0.002	0.0006	σ_y	0.001	0.0009
σ_c	0.006	0.0003	σ_c	0.006	0.0004
σ_h	0.007	0.0004	σ_h	0.005	0.0003
$\Lambda_{11}(\vartheta)$	0.271	0.134	A_{11}	0.000	0.001
$\Lambda_{12}(\vartheta)$	1.391	0.067	A_{12}	1.233	0.068
$\Lambda_{21}(\vartheta)$	0.649	0.077	A_{21}	-0.002	0.002
$\Lambda_{22}(\vartheta)$	0.652	0.049	A_{22}	0.665	0.060
$\Lambda_{31}(\vartheta)$	-0.378	0.057	A_{31}	0.014	0.002
$\Lambda_{32}(\vartheta)$	0.739	0.033	A_{32}	0.537	0.049
Deterministic trend					
Parameter	ML Estimate	SE	Parameter	ML Estimate	SE
η	1.005	0.001	η	1.005	0

As for consumption, the DFM specification attributes significant explanatory power to the consumption measurement shock, leaving 50% of the variance to the technology shock. By contrast, the RBC model's technology shock seems to explain most of the long-run consumption fluctuations, with 97.51% of the variance explained 40 quarters ahead.

Regarding hours worked, the technology shock in the RBC model explains a very small proportion of the total variance of hours (less than 50% one quarter ahead) and less for more distant horizons. In contrast, in the DFM especification the proportion of long-run variance explained by the technology shock is much higher, although it also decreases in the long term.

Table 8: Variance Decomposition

$DFM(\vartheta)$

	horizon						
	[0]	**1**	**4**	**8**	**12**	**20**	**40**
output	67.06	97.79	97.88	97.98	98.07	98.20	98.38
	(38.71)	(1.55)	(1.49)	(1.43)	(1.38)	(1.31)	(1.22)
consumption	99.89	49.46	64.26	77.78	85.62	92.84	97.51
	(0.17)	(4.33)	(7.00)	(7.81)	(6.52)	(3.82)	(1.40)
investment	21.08	80.59	84.24	87.19	88.85	90.40	91.26
	(28.72)	(4.84)	(4.20)	(4.08)	(4.05)	(4.27)	(5.27)
hours	9.23	44.20	41.47	38.12	35.10	30.01	21.71
	(9.60)	(3.98)	(4.40)	(5.04)	(5.64)	(6.49)	(7.13)

DFM

	horizon						
	[0]	**1**	**4**	**8**	**12**	**20**	**40**
output	98.81	99.78	99.89	99.91	99.91	99.91	99.91
	(1.78)	(0.27)	(0.14)	(0.12)	(0.12)	(0.12)	(0.12)
consumption	51.17	63.14	64.41	60.95	54.55	49.27	47.81
	(6.23)	(6.16)	(7.48)	(8.97)	(10.78)	(13.26)	(14.94)
investment	98.76	99.77	99.88	99.89	99.89	99.89	99.89
	(1.83)	(0.27)	(0.14)	(0.12)	(0.12)	(0.12)	(0.12)
hours	43.63	78.68	83.04	80.68	72.90	59.46	30.40
	(5.32)	(3.07)	(3.46)	(4.54)	(6.23)	(8.26)	(20.37)

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