News and Business cycles in an Open Economy with Financial Frictions *

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PRELIMINARY AND INCOMPLETE VERSION

Abstract

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1 Introduction

We analyze the role of financial frictions in generating business cycles in response to news about total factor productivity. The focus is on the propagation of news shocks in advanced small open economies. We make three significant contributions.

Our first contribution is to identify news shocks, using methodologies of both Barsky and Sims (2011) and Beaudry et al. (2011), for Australia, Canada, New Zealand and the United Kingdom. We find, in line with the previous VAR evidence for the US economy, that expected shocks about the future Total Factor Productivity generate business cycle co-movements in output, hours, consumption and investment. We also find that news shocks are associated with countercyclical current account dynamics.

Our second contribution is to develop a small open economy model with financial frictions that is able to replicate the positive co-movements identified in the data. For this purpose, we extend the Jermann and Quadrini (2012) model to an open economy setting. The financial friction in this model arises because firms need to arrange a working capital loan prior to production taking place. Access to finance is constrained by the firm’s net wealth position. We show that the financial friction in this model is vital in generating data-congruent co-movements between macroeconomic variables in response to news shocks.

Finally, we empirically validate our model by matching the impulse responses of the model to those obtained from the VARs. An attractive feature of our Limited Information Methodology is that the targets we want to match are observables. This allows us, once the structural parameters have been estimated, to identify the “strengths” and the “weaknesses” of the model and to derive some useful economic conclusions about the model. This does not seem so obvious in the full information case where the estimated vector minimizes the distance between the model and the true data generation process. Since that the latter is unknown, there no way to assess how big this distance is or/and what this implies the economics of the model.

2 News shocks in open economies

[To be completed]
the United Kingdom. To our best knowledge this is the first rigorous attempt of identifying news shocks in advanced open economies.

2.1 Construction of TFP series

In the process of identifying news shocks, particular attention has to be paid to the construction of the time series for total factor productivity. Our identification schemes require a TFP series that is not affected by changes in the intensity with which capital is used. Using publicly available data on capital utilization (from HAVER), hours worked as well as a constructed quarterly series for the capital stock, we are able to construct a Solow residual augmented by capital utilization.

2.2 The Time Series Model

In this section, we describe the structure of our time series model and VAR analysis.

The starting point of our empirical analysis is a vector autoregressive model of order $K - \text{VAR}(K)$

$$\tilde{y}_t = \sum_{i=1}^{K} \Theta_i \tilde{y}_{t-i} + u_t$$

(1)

where $u_t$ is the $N \times 1$ vector of reduced-form errors that is normally distributed with zero and $\Sigma$ variance-covariance matrix. The regression-equation representation of the latter system is

$$\mathbf{Y} = \mathbf{X} \Psi + \mathbf{V}$$

where $\mathbf{Y} = [\tilde{y}_{h+1}, \ldots, \tilde{y}_T]$ is a $N \times T$ matrix containing all the data points in $\tilde{y}_t$, $\mathbf{X} = \mathbf{Y}_{-h}$ is a $(NK) \times T$ matrix containing the $h$-th lag of $\mathbf{Y}$, $\Theta = [\Theta_1 \cdots \Theta_K]$ is a $N \times (NK)$ matrix, and $\mathbf{U} = [u_{h+1}, \ldots, u_T]$ is a $N \times T$ matrix of disturbances.

The model has seven variables and three lags and this immediately implies a large number of parameters, whose estimation poses serious difficulties even with 50 years of macroeconomic data. Classical inference techniques will deliver estimates that are subject to enormous uncertainty, meaning that Bayesian procedures are required. Priors are used to shrink the number of the estimated parameters by focusing on some of them and ignoring others. An obvious choice can be Minnesota type priors (??) since they shrink the VAR($K$) model towards independent autoregressive of order one.
AR(1) models. Furthermore, evidence provided by ? and ? suggest that large VAR models achieve very good forecasting properties when they combined with Minnesota type prior information.

The posterior inference is obtained as follows. It is assumed that the prior distribution of the VAR parameter vector has a Normal-Wishart conjugate form

\[ \theta|\Sigma \sim N(\theta_0, \Sigma \otimes \Omega_0), \quad \Sigma \sim IW(v_0, S_0), \]

where \( \theta \) is obtained by stacking the columns of \( \Theta \). The prior moments of \( \theta \) are given by

\[ E[(\Theta_k)_{i,j}] = \begin{cases} \delta_i = j, k = 1 \\ 0 & \text{otherwise} \end{cases}, \quad Var[(\Theta_k)_{i,j}] = \lambda \sigma_i^2 / \sigma_j^2, \]

and as it is explained by ? they can be constructed using the following dummy observations

\[
Y_D = \begin{pmatrix}
\text{diag}(\delta_1 \sigma_1, \ldots, \delta_N \sigma_N) \\
0_{N \times (K-1)N} \\
\vdots \\
\text{diag}(\sigma_1, \ldots, \sigma_N) \\
0_{1 \times N}
\end{pmatrix}
\quad \text{and} \quad
X_D = \begin{pmatrix}
J_K \otimes \text{diag}(\sigma_1, \ldots, \sigma_N) \\
0_{N \times NK} \\
\vdots \\
0_{1 \times NK}
\end{pmatrix}
\]

where \( J_K = \text{diag}(1, 2, \ldots, K) \) and \( \text{diag} \) denotes the diagonal matrix. The prior moments of (2) are just functions of \( Y_D \) and \( X_D \), \( \Theta_0 = Y_DX_D' (X_DX_D')^{-1}, \Omega_0 = (X_DX_D')^{-1}, S_0 = (Y_D - \Theta_0X_D)(Y_D - \Theta_0X_D)', \) \( \) \( v_0 = T_D - NK \). Finally, the hyper-parameter \( \lambda \) controls the tightness of the prior.

Since the normal-inverted Wishart prior is conjugate, the conditional posterior distribution of this model is also normal-inverted Wishart (?)

\[ \theta|\Sigma, Y \sim N(\bar{\theta}, \bar{\Sigma} \otimes \bar{\Omega}), \quad \Sigma|Y \sim IW(\bar{v}, \bar{S}), \]

where the bar denotes that the parameters are those of the posterior distribution.

Defining \( \hat{\Theta} \) and \( \hat{U} \) as the OLS estimates, we have that \( \Theta = (\Omega_0^{-1} \Psi_0 + YX')(\Omega_0^{-1} + X'X)^{-1}, \bar{\Omega} = (\Omega_0^{-1} + X'X)^{-1}, \bar{v} = v_0 + T, \) and \( \bar{S} = \hat{\Theta}XX'\hat{\Theta}' + \Theta_0\Omega_0^{-1}\Theta_0 + S_0 + \hat{U}\hat{U}' - \hat{\Theta}\bar{\Omega}^{-1}\hat{\Theta}'. \)

The values of the persistence – \( \delta_i \) – and the error standard deviation – \( \sigma_i \) – parameters of the AR(1) model are obtained from its OLS estimation. Sensitivity analysis reveals that the results are robust to different selections of VAR lags. Finally, \( \lambda \) has
been set equal to 4, implying relative loose priors.

2.3 Barsky and Sims (2011) Identification

Barsky and Sims (2011) assume that productivity is driven by two shocks: the unanticipated productivity shock, $\epsilon_t^\gamma$, and the anticipated news shock, $\epsilon_t^\psi$, where $j$ indicates the anticipation horizon. Hence, technology growth $\gamma_t = \ln\left(\frac{Z_t}{Z_{t-1}}\right)$ can be expressed as

$$\gamma_t = \rho_{\gamma,1}\gamma_{t-1} + \rho_{\gamma,2}\gamma_{t-2} + \rho_{\gamma,3}\gamma_{t-3} + \epsilon_t^\gamma + \epsilon_t^\psi.$$  (5)

Equation (5) shows that a univariate model is unable to recover the impact of the news shock, since a news shock that occurs today has an effect on technology in the $j$-ahead period, leaving the current technology unchanged. However, other variables may react instantaneously to the news shock, since rational expectations induce agents to react in advance to future anticipated shocks in order to maximize lifetime utility. Hence, we identify the effect of the news shock by employing a multivariate VAR model, which include variables that react to the news shock on impact. In addition, we identify news shocks by assuming that they explain future movements in TFP not accounted for by the unanticipated technology shock.

To implement this identification in the VAR model we proceed as follows. The moving average representation of the VAR($K$) model is

$$\tilde{y}_t = B(L)v_t.$$  (6)

The mapping between the reduced-form errors and the structural shocks is:

$$v_t = A\varepsilon_t,$$  (7)

with $AA' = \Sigma$, and the $h$ steps ahead forecast error can be expressed as

$$\tilde{y}_{t+h} - E_{t-1}\tilde{y}_{t+h} = \sum_{\tau=0}^{h} B_{\tau}\tilde{A}D\varepsilon_{t+h-\tau},$$  (8)

where $\tilde{A}$ is the lower triangular matrix derived from the Cholesky decomposition of $\Sigma$, and $D$ is an orthonormal matrix such that $DD' = I_{dy}$, where $I_{dy}$ is the $dy \times dy$ identity matrix. The contribution of the structural shock $j$ to the forecast variance of variable
\[ FVD_{i,j}(h) = \frac{e_i' \left( \sum_{\tau=0}^{h} B_{\tau} \tilde{A} D e_j e_j' D' B_{\tau}' \right) e_i}{e_i' \left( \sum_{\tau=0}^{h} B_{\tau} \Sigma B_{\tau}' \right) e_i} = \frac{\sum_{\tau=0}^{h} B_{i,\tau} \tilde{A} \tilde{d} \tilde{A}' B_{i,\tau}'}{\sum_{\tau=0}^{h} B_{i,\tau} \Sigma B_{i,\tau}'}, \]  

(9)

where \( e_i \) denotes the selection vector with one in the \( i \)-th place and zeros elsewhere.

We place \( \varepsilon_t^\gamma \) into the first element of the \( \varepsilon_t \) vector, and \( \varepsilon_{\psi,t-1}^\psi \) in to the second one. The assumption that TFP is solely driven by unanticipated and anticipated shocks, as in equation (5), implies that \( \varepsilon_{a,t} \) and \( \varepsilon_{\psi,t-1} \) account for all variation in TFP at different horizons, which yields:

\[ FVD_{1,1}(h) + FVD_{1,2}(h) = 1. \]  

(10)

However, it is unlikely that equation (10) holds at all horizons in a multivariate VAR model. Hence, as suggested by Barsky and Sims (2011), we select the second column of the impact matrix \( \tilde{A}D \) that comes as close as possible to making equation (10) hold over a finite set of horizons. This is achieved by solving the following optimization problem:

\[ \tilde{d}^* = \arg \max_H \sum_{h=0}^{H} FVD_{1,2}(h) \]  

subject to

\[ \tilde{A}(1,j) = 0 \quad \forall \ j > 1, \]  

(12)

\[ \tilde{d}(1,1) = 0, \]  

(13)

\[ \tilde{d}' \tilde{d} = 1. \]  

(14)

Equations (12) and (13) ensure that TFP does not respond contemporaneously to news shocks, while equation (14) implies that \( \tilde{d}^* \) is a column vector that belongs to an orthonormal matrix \( D \). Furthermore, the first two equations make \( FVD_{1,1}(h) \) independent from the selection of \( d \) and, consequently, this term drops from the objective function.

Motivated by the analysis of Beaudry et al. (2011) we set \( h \) equal to 120. In order to derive the posterior distribution of the responses and the forecast decomposition this identification scheme is implemented for each posterior draw.
2.4 Beaudry et al. (2011) Identification

Beaudry et al. (2011) maintain Barsky and Sims assumption that TFP is driven only by two shocks: the unanticipated and the anticipated news shock. However, the news shock is identified by restricting the sign of the stock prices contemporaneous response. In other words, a news shock in Beaudry et al. identification scheme has zero contemporaneous effect on TFP, while it rises stock prices on impact. Based on the discussion in the previous paragraph we are looking from the matrix $D$ that meets the latter conditions. In our case this is implemented by combining the algorithm proposed by $\text{??}$, which delivers the matrix $\mathcal{D}$ that satisfies the sign requirements, while the zero restriction is imposed by following the procedure suggested by $\text{??}$ and this gives the new matrix $\tilde{\mathcal{D}}$. Finally, we check whether $\tilde{\mathcal{D}}$ satisfies the sign restrictions if yes then we set $D = \tilde{\mathcal{D}}$, otherwise, we repeat the whole process until we find one.

Beaudry et al. experiment by imposing further sign restrictions to consumption and real interest rates, however, the results remain broadly unchanged.

3 Literature and model choice

TBC

4 A simple small open economy model with financial frictions

We extend the flexible price version of the model presented in Jermann and Quadrini (2012) into a small open economy setting. To turn a closed economy real business cycle model into a small open economy model requires only a few changes to be made to the structure of the model. In an open economy, the savings of households do not have to equal the borrowing by firms. The gap between savings and investment equals the current account balance. Unlike a closed economy, the gross or pre-tax interest rate faced by households and firms is exogenous in a small open economy setting. This rate is determined instead by the world interest rate and as well as a small risk premium to ensure a well defined steady state. See Schmitt-Grohe and Uribe (2003) for alternative ways to close small open economy models. Firms and households produce and consume a homogeneous good. This good is a perfect substitute for output produced in the rest
of the world. As a result, the terms of trade defined as the price of imports relative to exports is constant.

As in Jermann and Quadrini (2012), we introduce financial frictions into the environment in which domestic firms are operating. The household sector, on the other hand, faces a standard optimization problem.

4.1 Borrowing constrained firms

At any time $t$, the representative firm combines hired labour, $n_t$ and accumulated capital stock, $k_{t-1}$ in a Cobb-Douglas production function $F(z_t, k_{t-1}, n_t) = z_t k_{t-1}^{\alpha} n_t^{1-\alpha}$. The variable $z_t$ is the level of productivity which follows a stochastic AR(2) process with a positive growth steady state growth rate.

As in Jaimovich and Rebelo (2008) capital accumulation is subject to investment adjustment costs of the type proposed by Christiano et al. (2005)

$$k_t = (1 - \delta) k_{t-1} + i_t \left( 1 - \frac{\phi}{2} \left( \frac{i_t}{n_{t-1}} - \gamma \right)^2 \right)$$

(15)

where $i_t$ is investment, $\delta$ the depreciation rate of capita, $\phi$ a parameter capturing the curvature of the adjustment cost function, and $\gamma$ the steady state growth rate of the level of productivity.

As in Jermann and Quadrini (2012), firms can finance investment projects either by issuing equity, $d_t$, or debt, $b^f_t$. Reducing equity payouts to finance investment projects does not affect a firm’s tax liabilities in the same way as issuing new debt. As a result, firms prefer debt to equity finance in this model. This preference for debt finance is captured by a constant tax benefit, or subsidy. The effective interest rate faced by firms is $R_t = 1 + r_t (1 - \tau)$, where $r_t$ is the world rate of interest (adjusted by a net-debt elastic risk premium) and $\tau$ captures the tax benefit on debt issuance.

The firm has to make its payments to its workers, shareholders, and creditors, as well as undertake investment before revenues are realized. To cover this cash flow mismatch, the firm as to get an intra-temporal working capital loan equal to its production at the beginning of the period.

The firm can either pay its factors of production, produce and pay back the inter-temporal loan at the end of the period, or it can not produce, abscond with the loan and
default. To rule out the latter scenario, the firm is subject to the following enforcement constraint:

\[ \xi_t \left( k_t - \frac{b^f_t}{1 + r_t} \right) = F(z_t, k_{t-1}, n_t) \]  \hspace{1cm} (16)

where \( \xi_t \) denotes the probability that the lender can recover the full value of the firm’s capital stock in the case of a default.

A key feature that determines the effect of this enforcement constraint on the model economy is an assumed rigidity affecting the substitution between equity and debt. If we define total intra-temporal borrowing, \( l_t \), as:

\[ l_t = F(z_t, k_{t-1}, n_t) = w_t n_t + i_t + d_t + b^f_{t-1} - \frac{b^f_t}{R_t} \]

then the firm will always be able to keep the demand for intra-period loans, \( l_t \), constant simply by changing the composition between debt and equity finance. In this case, shocks that affect the firm’s ability to borrow intra-temporally will have no effect on the firm’s choice of labour input or investment.

To make sure the enforcement constraint is binding, Jermann and Quadrini (2012) introduce a cost of adjusting equity payouts. As we are interested in news about permanent productivity shocks, we assume the following equity payout cost function, which is consistent with long-run growth:

\[ \varphi(d_t) = \left( 1 + \kappa \left( \frac{d_t}{y_t} - \frac{d_y}{y} \right)^2 \right) d_t \]

where \( y_t \) denotes GDP, \( \kappa \) a positive adjustment cost parameter and variables without time subscripts denote values along the balanced growth path.

Given these adjustment costs, the firm’s budget constraint can be written as:

\[ F(z_t, k_{t-1}, n_t) - w_t n_t - i_t - b^f_{t-1} + \frac{b^f_t}{R_t} - \varphi(d_t) = 0. \]  \hspace{1cm} (17)

The firm’s optimization problem consists of maximizing equity payouts, subject to the
budget (17), capital accumulation (15) and enforcement (16) constraints.

\[ L = E_0 \sum_{t=0}^{\infty} \beta^t \lambda_t d_t \]
\[ + E_0 \sum_{t=0}^{\infty} \beta^t q_t \left( F(z_t, k_t, n_t) - w_t n_t - \beta^t b_t - b_t \frac{R_t}{1 + r_t} - \varphi(d_t) \right) \]
\[ + E_0 \sum_{t=0}^{\infty} \beta^t v_t \left( i_t \left( 1 - \phi \left( \frac{i_t}{i_{t-1}} - \gamma \right) \right) - k_t + (1 - \delta) k_{t-1} \right) \]
\[ + E_0 \sum_{t=0}^{\infty} \beta^t \mu_t \left( \xi_t \left( k_t - b_t \frac{R_t}{1 + r_t} \right) - F(z_t, k_{t-1}, n_t) \right) \]

The variable \( \lambda_t \) denotes the marginal utility of consumption of households, who are the owners of the firm. The variables \( q_t, v_t \) and \( \mu_t \) are the Lagrange multipliers on constraints (17), (15) and (16), respectively. The first order conditions for the optimal choice of labour, inter-temporal borrowing, capital and investment are:

\[ (1 - \Delta_t \varphi'(d_t)) F_{n,t} = w_t \] (18)
\[ \beta \frac{\lambda_{t+1}}{\lambda_t} \varphi'(d_t) R_t + \Delta_t \varphi'(d_t) \frac{R_t}{1 + r_t} = 1 \] (19)
\[ \beta \frac{\lambda_{t+1}}{\lambda_t} \varphi'(d_t) \left( F_{k,t} \left( 1 - \Delta_{t+1} \varphi'(d_{t+1}) \right) + Q_{t+1} (1 - \delta) + \Delta_t \varphi'(d_t) \xi_t \right) = Q_t \] (20)
\[ Q_t \left( 1 - \frac{\phi}{\frac{i_t}{i_{t-1}} - \gamma} \right) - \phi \left( \frac{i_t}{i_{t-1}} - \gamma \right) + \beta Q_{t+1} \frac{\lambda_{t+1}}{\lambda_t} \varphi'(d_{t+1}) \varphi'(d_t) \left( i_{t+1} - 1 \right) \left( \frac{i_{t+1}}{i_t} \right)^2 = 1 \] (21)

where we define the following composite variables: \( Q_t = \frac{w_t}{\lambda_t} \varphi'(d_t) \), \( \Delta_t = \frac{w_t}{\lambda_t} \), and \( \frac{\lambda_t}{\varphi'(d_t)} = q_t \).

4.2 Households

The representative household maximizes the expected utility function defined over

\[ E_0 \sum_{t=0}^{\infty} \beta^t U(c_t, n_t) \] (22)

consumption, \( c_t \), and labour effort, \( n_t \). The household’s discount factor is denoted by \( beta \) and has the usual properties that \( 0 < \beta < 1 \).

Expected utility is maximized subject to the following budget constraint:

\[ w_t n_t + d_t + b_{t-1} = \frac{b_t}{1 + r_t} + c_t + T_t. \] (23)
At the beginning of each period, the household receives wage income, \( w_t n_t \), and a dividend payment, \( d_t \). The household also holds a stock of internationally traded bonds, \( b_{t-1} \). The household’s income stream is used to purchase consumption goods, pay taxes, \( T_t \), and purchase new bonds, \( b_t \) at a price of \( 1/(1+r_t) \) per unit. Taxation is used to finance the tax benefit enjoyed by firms when borrowing. \( T_t = b_t^f/R_t - b_t^f/(1+r_t) \).

Given the household’s decision problem over consumption, labour effort and bond holdings,

\[
H = E_0 \sum_{t=0}^{\infty} \beta^t U(c_t, n_t) + E_0 \sum_{t=0}^{\infty} \beta^t \lambda_t \left[ w_t n_t + b_t + \frac{b_{t+1}}{1+r_t} - c_t - T_t \right]
\]

the usual first-order conditions are:

\[
U_c(c_t, n_t) - \lambda_t = 0 \tag{25}
\]

\[
U_n(c_t, n_t) + \lambda_t w_t = 0 \tag{26}
\]

\[
\frac{\beta \lambda_{t+1}}{\lambda_t} (1+r_t) = 1 \tag{27}
\]

### 4.3 Consolidated budget constraint

Combining the budget constraints of the representative firm (17) with that of the representative household (.), yields the economy wide budget constraint:

\[
F(z_t, k_{t-1}, n_t) = c_t + i_t + \frac{(b_t - b^f_t)}{1+r_t} - (b_{t-1} - b^f_{t-1}) + \varphi(d_t) - d_t \tag{28}
\]

Where the net foreign asset position is defined as the difference between household savings and firm borrowing, \( (b_t - b^f_t) \). The trade balance, which we assume to be zero in the steady state, is defined as:

\[
TB_t = y_t - c_t - i_t - \varphi(d_t) - d_t
\]

### 5 News about total factor productivity in the JQ model

Financial frictions of the form suggested by JQ can address the co-movement puzzle between consumption and labour following an anticipated shock to future total factor productivity. In the standard RBC model, the wealth effect associated with a news shock raises consumption but lowers labour effort. Given the following consumption...
labour trade-off:

\[ w_t = \frac{n_t^\eta}{c_t^\sigma} \]

labour effort has to fall if consumption rises without an offsetting increase in the real wage. In the RBC model, the wage rate is simply equal to the marginal product of labour, which depends on actual, not anticipated TFP.

\[ F_n(z_t, k_t, n_t) = \frac{n_t^\eta}{c_t^\sigma} \]

In the JQ model, financial frictions in conjunction with dividend adjustment costs can generate positive co-movement between consumption and labour effort. The relationship between the real wage and the marginal product of labour is augmented by a term capturing the tightness of the firm’s intra-period borrowing constraint.

\[ F_n(z_t, k_t, n_t)(1 - \frac{\mu_t}{\lambda_t} \phi'(d_t)) = \frac{n_t^\eta}{c_t^\sigma} \]

Following a positive news shock about TFP, the term \( \frac{\mu_t}{\lambda_t} \phi'(d_t) \) falls, which for a given marginal product of labour raises the real wage. The rise in the real wage causes agents to increase hours worked and thus output to rise.

The intuition is that the investment boom triggered by a news shock in an open economy causes the firm to reduce dividend payments. As dividend payments have to be financed via a working capital loan, a reduction in dividends relaxes the borrowing constraint faced by firms when borrowing working capital. The term \( \frac{\mu_t}{\lambda_t} \) is the Lagrange multiplier on the borrowing constraint faced by the firm. As the constraint is relaxed, the value of multiplier falls.

To understand why the term \( \frac{\mu_t}{\lambda_t} \phi'(d_t) \) declines following a news shock, we need to consider what is happening to investment following a news shock. We know from Jaimovic and Rebello that in a small open economy model investment rises following a news shock. In the JQ model, there are two ways a firm can finance an increase in investment: via debt \( (b_{t+1}^f) \) or via a reduction in dividend payouts, \( (d_t) \). Because of the tax treatment of dividends relative to debt, the firm always prefers to borrowing to equity financing. A further reason the firm prefers inter-temporal borrowing is that changing the rate at which dividends are paid out is costly. This cost is represented
by

\[ \phi(d_t) = d_t + \kappa (d_t - \bar{d})^2 \]

The firm’s borrowing constraint, (\ref{eq:firm_borrowing}), implies that for output to rise following a news to TFP shock, next period’s capital stock must be higher than this period’s borrowing.

\[ \xi_t \left( k_{t+1} - \frac{b_{t+1}^f}{1 + r_t} \right) = y_t \]

Therefore, for output to increase following a news shock, part of the new investment must be financed through a reduction in dividend payouts. As changing the rate of investment is costly due to CEE investment adjustment costs, investment is rising and dividends are falling between the announcement and realization of the increase in TFP.

If we combine equations (\ref{eq:firm_borrowing}) and (\ref{eq:output_equation}):

\[ \left( \frac{\phi'(d_t)}{\phi'(d_{t+1})} \right) \frac{R_t}{1 + r_t} + \frac{\mu_t}{\lambda_t} \phi'(d_t) \xi_t \frac{R_t}{1 + r_t} = 1 \]

and make the assumption that in a small open economy, the interest rate is exogenous, so that neither \( R_t \) nor \( 1 + r_t \) change in response to a news shock, then we can easily show that \( \frac{\mu_t}{\lambda_t} \phi'(d_t) \) is falling since \( \left( \frac{\phi'(d_t)}{\phi'(d_{t+1})} \right) \) must be rising.

6 Model versus Data

6.1 DSGE Model Estimation

The next step required for making our model able to serve the purposes of our analysis is to decide about the magnitude of the structural parameters. Similar to \( \ldots \), Christiano et al. (2005) and \( \ldots \) we use limited information (LMI) techniques to estimate them. Before the evolution of the MCMC methodology DSGE models were mainly estimated using classical LMI methods and this was due to their good small samples properties (\ref{eq:small_samples}), the lack of the requirement the structural model to be viewed as the true data generation process and the non-smoothness of the DSGE likelihood.

As it is explained in \( \ldots \), the most attractive feature of the LMI methodology is that you actually observe the targets you are trying to “hit”. This allows you to identify the “strengths” and the “weaknesses” of the model, once the structural parameters have been estimated, and to derive some useful economic conclusions about the model.
This does not seem so obvious in the full information case where the estimated vector minimizes the distance between the model and the true data generation process. Since that the latter is unknown, there no way to assess how big this distance is or/and what this implies the economics of the model.

Collecting all the VAR variable responses after a risk news shock for all periods in one vector, say, $\hat{R}$ and doing the same for the DSGE ones, $R(\theta)$, then we can select the structural parameter vector that minimises the following norm

$$\theta = \arg \min \left( \hat{R} - R(\theta) \right)^\prime W \left( \hat{R} - R(\theta) \right)$$

(29)

where $\hat{R}$ corresponds to the median of the posterior distribution of the VAR identified responses and $W$ is the inverse of the diagonal matrix of the variance-covariance matrix of the posterior distribution of the VAR identified responses.
Figure 1: News about TFP in New Zealand

Note: Barsky and Sims identification method
Note: Beaudry identification method
Figure 3: News about TFP in Australia

Note: Barsky and Sims identification method
Figure 4: News about TFP in Australia

Note: Beaudry identification method
Figure 5: News about TFP in Canada

Note: Barsky and Sims identification method
Figure 6: News about TFP in Canada

Note: Beaudry identification method
Figure 7: News about TFP in the United Kingdom

Note: Barsky and Sims identification method
Figure 8: News about TFP in the United Kingdom

Note: Beaudry identification method
Figure 9: News about total factor productivity

Note: Dashed line shows the response of our baseline model to a TFP shock that is expected to occur in period 3. The solid line shows the response to the same shock when kappa, the dividend adjustment cost, is set to zero.
Figure 10: Data Versus Data: New Zealand

Note: Barsky and Sims identification method

Figure 11: Data Versus Data: Australia

Note: Barsky and Sims identification method
Figure 12: Data Versus Data: Canada

Figure 13: Data Versus Data: United Kingdom

Note: Barsky and Sims identification method
Figure 14: Data Versus Data: New Zealand

Note: Beaudry identification method

Figure 15: Data Versus Data: Australia

Note: Beaudry identification method
Figure 16: Data Versus Data: Canada

Note: Beaudry identification method

Figure 17: Data Versus Data: United Kingdom

Note: Beaudry identification method
7 Tables

Table 1: Barsky and Sims

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Table 2: Beaudry

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<td>0.0002</td>
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8 Sensitivity analysis

9 Conclusion

References


A  Steady States

\[ R^h = \frac{\gamma}{\beta} \]  

(30)

\[ \frac{k}{i} = \frac{\gamma}{\gamma - 1 + \delta} \]  

(31)

\[ \frac{\mu}{\lambda} = \frac{\gamma - \beta R R^h}{\gamma \xi R} \]  

(32)

\[ \frac{y}{k} = \frac{(1 - \frac{\mu}{\lambda} \xi) \frac{\gamma}{\beta} - 1 + \delta}{(1 - \frac{\lambda}{\xi}) \theta \gamma} \]  

(33)

\[ k = \left( \frac{\frac{y}{k}}{\frac{\lambda}{\xi} n^{1-\theta}} \right)^{\frac{1}{\theta-1}} \]  

(34)

\[ b^f = \left( k - \frac{y}{\xi} \right) R^h \]  

(35)

\[ (1 - \theta) \frac{y}{n} \left( 1 - \frac{\mu}{\lambda} \right) = w \]  

(36)

\[ y - wn - i + b^f \left( \frac{1}{R} - \frac{1}{\gamma} \right) = d \]  

(37)

\[ b = b^f \]  

(38)

\[ wn + b \left( \frac{1}{\gamma} - \frac{1}{R} \right) + d = c \]  

(39)

\[ \frac{1}{c} = \lambda \]  

(40)

\[ \frac{\lambda w}{n^n} = \alpha \]  

(41)

A.1  Summary of Stationary Equations

\[ \frac{1}{c_t} - \lambda_t = 0 \]

\[ -\alpha n_t^\eta + \lambda_t w_t = 0 \]

\[ \frac{\beta \lambda t + 1}{\lambda t \gamma t + 1} R_t^h = 1 \]

\[ w_t n_t + \frac{b_{t-1}}{\gamma_t} + d_t = \frac{b_t}{R_t} + c_t \]
\[
y_t = A_t \left( \frac{k_{t-1}}{\gamma_t} \right)^\theta n_t^{1-\theta}
\]
\[
F_t(z_t, k_{t-1}, n_t) = (1 - \theta) \frac{y_t}{n_t}
\]
\[
F_k(z_t, k_{t-1}, n_t) = \theta \gamma_t \frac{y_t}{k_{t-1}}
\]
\[
(1 - \theta) \frac{y_t}{n_t} \left( 1 - \frac{\mu_t}{\lambda_t} \varphi'(d_i) \right) = w_t
\]
\[
\frac{\beta \lambda_{t+1}}{\lambda_t \gamma_{t+1}} \left( \frac{\varphi'(d_{t})}{\varphi'(d_{t+1})} \right) R_t + \frac{\mu_t}{\lambda_t} \varphi'(d_i) \xi_t \frac{R_t}{R^h_t} = 1
\]
\[
\frac{\beta \lambda_{t+1}}{\lambda_t \gamma_{t+1}} \left[ q_{t+1}(1 - \delta) + \left( 1 - \frac{\mu_{t+1}}{\lambda_{t+1}} \varphi'(d_{t+1}) \right) \theta \gamma_{t+1} \frac{y_{t+1}}{k_{t+1}} \right] + \frac{\mu_t}{\lambda_t} \varphi'(d_i) \xi_t = q_t
\]
\[
\varphi(d_t) = \left( 1 + \kappa \left( \frac{d_t}{y_t} - \frac{d}{y} \right)^2 \right) d_t
\]
\[
\varphi'(d_t) = \left( 1 + \kappa \left( \frac{d_t}{y_t} - \frac{d}{y} \right)^2 \right) + 2 \kappa \left( \frac{d_t}{y_t} - \frac{d}{y} \right) \frac{d_t}{y_t}
\]
\[
\varphi'(d_t) = 1 + 2 \kappa \left( \frac{d}{y} \right)^2 \left( \hat{d}_t - \hat{y}_t \right)
\]
\[
\frac{\varphi'(d_t) - \varphi'(d)}{\varphi'(d)} = 2 \kappa \left( \frac{d}{y} \right)^2 \left( \hat{d}_t - \hat{y}_t \right)
\]
\[
\varphi' \left( \hat{d}_t \right) = 2 \kappa \left( \frac{d}{y} \right)^2 \left( \hat{d}_t - \hat{y}_t \right)
\]
\[
y_t - w_t n_t - i_t - b_{t-1}^f \gamma_t + b_t^f \frac{R_t}{R^h_t} - \varphi'(d_t) = 0
\]
\[
\xi_t \left( k_t - \frac{b_t^f}{R^h_t} \right) = y_t
\]
\[ R_t^h = R^h - \psi \left( e^{\left( \frac{\gamma_{t-1}}{\lambda} \frac{\gamma_t}{\gamma_t} \right)} - 1 \right) \]

\[ k_t = (1 - \delta) \frac{k_{t-1}}{\gamma_t} + \left( 1 - \frac{\phi}{2} \left( \frac{i_t}{\gamma_{t-1}} - \gamma \right) \right) i_t \]

\[ 1 = q_t \left( 1 - \frac{\phi}{2} \left( \frac{i_t}{\gamma_{t-1}} - \gamma \right) \right)^2 - \phi \left( \frac{i_t}{\gamma_{t-1}} - \gamma \right) + 1 + \beta \frac{\lambda_{t+1}}{\lambda_t \gamma_{t+1}} q_{t+1} \phi \left( \frac{i_{t+1}}{\gamma_{t+1}} - \gamma \right) \left( \frac{i_{t+1}}{\gamma_{t+1}} \right)^2 \]

**B Linearised Model**

\[ \hat{\lambda}_t = -\hat{\epsilon}_t \]

\[ \hat{n}_t = \frac{1}{\eta} \left( \hat{\lambda}_t + \hat{\omega}_t \right) \]

\[ 0 = \hat{\lambda}_{t+1} - \hat{\lambda}_t - \hat{\gamma}_{t+1} + \hat{R}_t^h \]

\[ \frac{w_n}{c} (\hat{\omega}_t + \hat{n}_t) + \frac{b}{c} \left( \hat{b}_{t-1} - \hat{\gamma}_t \right) + \frac{d}{c} \hat{d}_t - \frac{b}{c R} (\hat{b}_t - \hat{R}_t) = \hat{\epsilon}_t \]

\[ \hat{y}_t = \hat{A}_t + \theta \left( \hat{k}_{t-1} - \hat{\gamma}_t \right) + (1 - \theta) \hat{n}_t \]

\[ (1 - \frac{\mu}{\lambda}) (\hat{y}_t - \hat{n}_t) - \frac{\mu}{\lambda} \left( \hat{\mu}_t - \hat{\lambda}_t + \phi'(\hat{d}_t) \right) = \hat{\omega}_t \]

\[ 0 = \frac{\beta}{\gamma} R \left( \hat{\lambda}_{t+1} - \hat{\lambda}_t - \hat{\gamma}_{t+1} + \phi'(\hat{d}_t) - \phi'(\hat{d}_{t+1}) + \hat{R}_t \right) \]

\[ + \frac{\mu}{\lambda} \xi R^h \left( \hat{\mu}_t - \hat{\lambda}_t + \phi'(\hat{d}_t) + \hat{\xi}_t + \hat{R}_t - \hat{R}_t^h \right) \]

\[ \frac{\beta \lambda_{t+1}}{\lambda_t \gamma_{t+1}} \left( \frac{\phi'(d_t)}{\phi'(d_{t+1})} \right) \left[ q_{t+1}(1 - \delta) + \left( 1 - \frac{\mu_{t+1}}{\lambda_{t+1}} \phi'(d_{t+1}) \right) \theta_{t+1} \frac{y_{t+1}}{k_t} \right] + \frac{\mu}{\lambda} \xi R^h \left( \hat{\mu}_t - \hat{\lambda}_t + \phi'(\hat{d}_t) + \hat{\xi}_t + \hat{R}_t - \hat{R}_t^h \right) \]
\[
\dot{q}_t = \frac{(1-\delta)\beta}{\gamma} \left( \hat{\lambda}_{t+1} - \hat{\lambda}_t + \hat{\gamma}_{t+1} + \varphi'(\hat{d}_t) - \varphi'(\hat{d}_{t+1}) + \hat{q}_{t+1} \right) \\
+ \frac{\beta \theta y}{k} \left( \hat{\lambda}_{t+1} - \hat{\lambda}_t + \varphi'(\hat{d}_t) - \varphi'(\hat{d}_{t+1}) + \hat{y}_{t+1} - \hat{k}_t \right) \\
- \frac{\beta \theta y \mu}{k \lambda} \left( -\hat{\lambda}_t + \varphi'(\hat{d}_t) + \hat{\mu}_{t+1} + \hat{y}_{t+1} - \hat{k}_t \right) \\
+ \frac{\mu}{\lambda} \xi \left( \hat{\mu}_t - \hat{\lambda}_t + \varphi'(\hat{d}_t) + \hat{\xi}_t \right)
\] (50)

\[
\varphi'(d_t) = 2 \kappa \left( \frac{d}{y} \right)^2 (\hat{d}_t - \hat{y}_t)
\] (51)

\[
\dot{y}_t - \frac{wn}{y} (\hat{w}_t + \hat{n}_t) - \frac{i}{y} \hat{t}_t - \frac{b^f}{y \gamma} \left( \hat{b}^f_{t-1} - \hat{\gamma}_t \right) + \frac{b^f}{y R} \left( \hat{b}^f_t - \hat{R}_t \right) - \frac{d}{y} \hat{d}_t = 0
\] (52)

\[
\frac{\xi k}{y} (\hat{\xi}_t + \hat{\kappa}_t) = \frac{\xi b^f}{y R^h} \left( \hat{\xi}_t + \hat{b}^f_t - \hat{R}_t^h \right) = \hat{y}_t
\]

\[
\hat{R}_t^h = -\psi \frac{b}{R^h} \left( b_{t-1} - b^f_{t-1} \right)
\]

\[
\hat{\kappa}_t = \frac{1-\delta}{\gamma} (\hat{k}_{t-1} - \hat{\gamma}_t) + \frac{i}{k} \hat{\eta}_t
\]

\[
\hat{\eta}_t = \frac{1}{1 + \beta} (\hat{\eta}_{t-1} - \hat{\gamma}_t) + \frac{\beta}{1 + \beta} (\hat{\eta}_{t+1} + \hat{\gamma}_{t+1}) + \frac{1}{(1 + \beta) \phi \gamma^2} \hat{q}_t
\] (53)