

Solving Dynamic Equilibrium Models by a Method of Undetermined Coefficients

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Abstract

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ABSTRACT

I present an undetermined coefficients method for obtaining a linear approximating to the solution of a dynamic, rational expectations model. I also show how that solution can be used to compute a model's implications for impulse response functions and for second moments.

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1. Introduction

This paper describes a method for solving a system of linear expectational difference equations. The output of the method is a feedback rule relating the current period endogenous variables to a set of state variables. The method, a matrix version of the undetermined coefficients method described in Christiano (1991, Appendix), has been used extensively in applications where the expectational difference equations correspond to the linearized Euler equations of dynamic rational expectations models.¹ It is a blend of the undetermined coefficients method described in McCallum (1983) and the approach of Blanchard and Kahn (1980) (see also King, Plosser and Rebelo (1987)).² Because the method focuses on Euler equations, it is not limited to models whose solution can be expressed as the solution to a planning problem. Thus, it can handle models with tax and other distortions.

A distinguishing characteristic of the method is that it can easily accommodate a class of models in which different time t endogenous variables are based on different information sets. This class of models includes limited participation models of money, models of labor hoarding and models with sticky prices.³ The range of applications is not limited to these models, however. The method can handle any model which does not have occasionally binding inequality constraints.⁴ For example, an exciting recent development in macroeconomics is the study of general equilibrium models with heterogeneity. A significant breakthrough in the

¹A selection of papers which apply the method includes Alexopoulos (1997), Chari, Christiano and Eichenbaum (1995), Chari, Kehoe and McGrattan (1996), Christiano (1991), Christiano and Eichenbaum (1992, 1995), Christiano, Eichenbaum and Evans (1997a), Fisher (1997), Gust (1997) and Schlagenhauf and Wrase (1995).

²For another approach, see Uhlig (1997).

³The limited participation models I have in mind include those in Chari, Christiano and Eichenbaum (1995), Christiano (1991), Christiano and Eichenbaum (1992), Christiano, Eichenbaum and Evans (1997a), Fuerst (1992) and Schlagenhauf and Wrase (1995), in which a financial decision by households is made prior to the realization of the current period shocks, but other decisions are made afterward. Labor hoarding models include those of Burnside and Eichenbaum (1996) and Burnside, Eichenbaum and Rebelo (1993), in which the number of people working is determined prior to the realization of a current period shock, while the intensity with which they work is decided afterward. Other examples include sticky price models in which at least some price setters set prices before the realization of a monetary shock and other decisions are made afterward (see, for example, Chari, Kehoe and McGrattan (1996), Christiano, Eichenbaum and Evans (1997) and Gust (1997).)

⁴For a discussion of strategies for solving such models, see Christiano and Fisher (1997).

quantitative analysis of these models was achieved by Jeff Campbell (1997), when he showed that a class of these models can be solved by linearization methods. We show below how the method presented here can be applied to solve Jeff Campbell's model. Straightforward modifications of the discussion there can be applied to solve the general equilibrium model with worker heterogeneity analyzed by Monika Merz (1996).

Section 2 of the paper presents the expectational difference equations considered and defines precisely what I mean by a solution. Section 3 discusses the computational strategy for finding the solution. The system of expectational difference equations and the solution is presented in full generality, so that the notation is sometimes complicated. For this reason, section 4 presents a series of examples to illustrate aspects of the method. The first example exhibits the method in the simplest possible setting, the one sector stochastic growth model in which hours worked are constant. It shows how the expectational difference equations that are the focus of the method can arise by linearizing the Euler equations of a nonlinear model. The next three examples illustrate various technical aspects of the method. The fifth example shows how the method can be used to solve Campbell's model. Section 5 briefly discusses methods for using the model solution to compute impulse response functions and second moments. Section 6 presents some concluding remarks.

2. A System of Expectational Difference Equations

This section defines a system of expectational difference equations and defines a solution. A solution is a linear feedback rule relating the current period endogenous variables to a set of state variables. It is characterized by two matrices. These two matrices can be understood by dividing up the current period state variables into two sets. The first set, the endogenous state variables, are variables like capital which are predetermined at the beginning of the current period, but were determined by the model in some previous period. The second set, the exogenous state variables, are variables that are generated outside the model by some stochastic process. The first matrix considered in the solution strategy (the 'feedback part') is the one that characterizes the impact of the endogenous state variables on the current period endogenous variables. The second matrix (the 'feedforward part') characterizes the impact of the current period exogenous variables on the current period endogenous variables. The procedure for computing these two matrices is

described in detail in the next section.

Let z_{1t} denote an $n_1 \times 1$ vector of endogenous variables that is determined at time t . Let the $n \times 1$ vector z_t be defined as follows:

$$z_t = \begin{bmatrix} z_{1t} \\ z_{2t} \end{bmatrix}, \quad (2.1)$$

where z_{2t} is a $qn_1 \times 1$ vector of q lagged z_{1t} 's and $n \equiv n_1(q+1)$. The number of lags of z_{1t} included in z_{2t} is defined by the condition that z_t contain all endogenous state variables relevant for the determination of z_{1t+1} at time $t+1$.⁵ We can accommodate $q=0$, in which case $z_t \equiv z_{1t}$. The elements in z are expressed as deviations from their respective nonstochastic steady state values.

Suppose that z_t satisfies the following system of n_1 linear expectational difference equations:

$$\mathcal{E}_t \left[\sum_{i=0}^r \alpha_i z_{t+r-1-i} + \sum_{i=0}^{r-1} \beta_i s_{t+r-1-i} \right] = 0, \quad (2.2)$$

for $t=0, 1, \dots$, and for given z_{-1} . Here, s_t is an $m \times 1$ vector of exogenous shocks. I explain below how this is constructed from current and lagged values of the shocks, θ_t , to agents' environment. In (2.2), $r > q$, and the α_i 's and β_i 's are given $n_1 \times n$ and $n_1 \times m$ matrices, respectively. Also, when $q > 0$, the right qn_1 columns of α_i , $i=0, \dots, r-1$ are composed of zeros. Assume that the rank of α_0 exceeds 0 and that the $n_1 \times (r+1)n$ dimensional matrix, $[\alpha_0, \alpha_1, \dots, \alpha_r]$ has full row rank.⁶

The symbol \mathcal{E}_t in (2.2) represents an expectation operator. This operator differs from the normal expectation operator, E_t , in that it allows the conditioning information set to vary across the equations in (2.2). That is, if X_t is an $n_1 \times 1$ vector of random variables,

$$\mathcal{E}_t[X_t] \equiv \begin{bmatrix} E[X_{1t}|\Omega_{1t}] \\ \vdots \\ E[X_{n_1t}|\Omega_{n_1t}] \end{bmatrix}, \quad (2.3)$$

where $E[X|\Omega]$ denotes the mathematical expectation of the random variable X conditional on the information set, Ω . In the *standard case*, all the Ω_{it} 's are

⁵For an illustration of the possibility, $q > 0$, see example 4 in section 4.

⁶For an illustration of how (2.2) can arise by linearizing the Euler equations of an economic model, see example 1 in section 4 below.

identical, with $\Omega_{it} = \{z_{t-1-k}, \theta_{t-k}; k \geq 0\}$ for all i . The specification of (2.2) is designed to accommodate models in which different time t endogenous variables are determined based on different information sets.⁷ It is convenient to adopt a simple vector characterization of the information structure in (2.2). Let τ_i denote the column vector with unity in locations corresponding to elements of θ_t which are contained in Ω_{it} and zero in locations corresponding to elements of θ_t which are excluded from Ω_{it} , $i = 1, \dots, n_1$. Also, let $\tau = [\tau_1, \dots, \tau_{n_1}]$.

The law of motion of s_t has the following form:

$$s_t = P s_{t-1} + \epsilon_t, \quad (2.4)$$

where ϵ_t has mean zero and is uncorrelated with ϵ_{t-l} , s_{t-l} , $l > 0$, and is derived from the time series representation for θ_t . I assume:

$$\theta_t = \rho \theta_{t-1} + e_t, \quad E e_t e_t' = V_e, \quad (2.5)$$

where the zero-mean random variable e_t is uncorrelated with lagged values of itself and of θ_t .⁸ In the standard case,

$$s_t = \theta_t, \quad P = \rho, \quad \epsilon_t = e_t.$$

If any one of the information sets, Ω_{it} , $i = 1, \dots, n_1$ does not contain the whole of θ_t , then (2.4) is constructed slightly differently:

$$s_t = \begin{pmatrix} \theta_t \\ \theta_{t-1} \end{pmatrix}, \quad P = \begin{bmatrix} \rho & 0 \\ I & 0 \end{bmatrix}, \quad \epsilon_t = \begin{pmatrix} e_t \\ 0 \end{pmatrix}.$$

We seek a $\{z_t\}$ process which is consistent with (2.1) - (2.4) for all z_{t-1}, s_t ; with the initial condition, z_{-1} ; and with the condition:

$$\lim_{j \rightarrow \infty} E_t z_{t+j} \rightarrow 0. \quad (2.6)$$

⁷This possibility is illustrated in example 3.

⁸This law of motion is quite general and will accommodate an arbitrary ARMA(p,q) representation for the underlying economic shocks. For example, suppose $p = q = 1$ and $x_t = \phi x_{t-1} + \varepsilon_t - \gamma \varepsilon_{t-1}$, where x_t is a shock to the economic environment. Then,

$$\theta_t = \begin{pmatrix} x_t \\ \varepsilon_t \end{pmatrix}, \quad \rho = \begin{bmatrix} \phi & -\gamma \\ 1 & 0 \end{bmatrix}, \quad e_t = \begin{pmatrix} \varepsilon_t \\ 0 \end{pmatrix}.$$

The assumption that θ_t has mean zero is also without loss of generality, since we are free to interpret θ_t as being expressed in deviation from mean.

The latter restriction could be motivated by the underlying economic model. In any case, a solution that is not consistent with this condition is not generally of interest. This is because, in practice, the function whose expectation is being taken in (2.2) is a linear approximation of a non-linear function, and the quality of this approximation can be expected to deteriorate as z_t diverges substantially from 0. For a further discussion, see example 1 in section 4 below.

We limit ourselves to solutions which have the following representation:

$$z_t = Az_{t-1} + Bs_t, \quad (2.7)$$

where A is the feedback part of the solution and B is the feedforward part. Here, the $n \times n$ matrix A has the following structure:

$$A = \begin{bmatrix} A_1 \\ \cdots \\ A_2 \end{bmatrix},$$

where A_1 is an $n_1 \times n$ matrix of (as yet) undetermined coefficients and A_2 is the $(n - n_1) \times n$ matrix:

$$A_2 = \begin{bmatrix} I & 0 & \cdots & 0 & 0 \\ 0 & I & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & I & 0 \end{bmatrix}. \quad (2.8)$$

Here, $A_1 \equiv A$ when $q = 0$. In (2.8), I and 0 denote the n_1 -dimensional identity and zero matrices, respectively. The requirement, (2.6), corresponds to the restriction that the eigenvalues of A be strictly less than unity in absolute value.

The n by m matrix B has the following structure:

$$B = \begin{bmatrix} B_1 \\ \cdots \\ B_2 \end{bmatrix}. \quad (2.9)$$

Here, B_1 is an $n_1 \times m$ matrix composed primarily of as-yet undetermined coefficients, and B_2 is an $(n - n_1) \times m$ matrix of zeros. When $q = 0$, then $B \equiv B_1$. Under the standard assumption about information sets, all elements of B_1 are treated as undetermined coefficients. When information sets differ, a number of elements of B_1 are set to zero. We assume that the variables in z_{1t} are ordered so

that if the l^{th} entry in τ_i is zero, then the $(i, l)^{th}$ entry of B_1 is also restricted to be zero. For example, if the i^{th} equation is the Euler equation associated with some variable, then we assume that that variable occupies the i^{th} position in z_{1t} . It is natural then, that the policy rule governing that variable exclude the l^{th} element of s_t .⁹

In summary, the following objects define the system of expectational difference equations that is addressed in this paper:

$$\rho, \alpha_0, \dots, \alpha_r, \beta_0, \dots, \beta_r. \quad (2.10)$$

To find a solution, no further information is needed if the standard assumption about information sets is made. If there is incomplete information in at least one equation in (2.2), then one needs to also specify τ and V_e . In this case, V_e is required only if there is a non-trivial signal extraction problem to solve. This occurs if (i) in one of the equations with incomplete information, some current period exogenous variables are observed and some are not, and (ii) the V_e matrix is non-diagonal.

3. An Undetermined Coefficient Solution Method

I describe a strategy for computing the undetermined coefficients in the feedback part, A , and the feedforward part, B , of the policy rule. I first derive a set of equations that A and B must satisfy if (2.7) is to be consistent with (2.1) - (2.4)

⁹Not all model formulations necessarily lead to zero restrictions on B_1 . A non-zero restriction can arise if a variable has been scaled by an exogenous variable in a particular way. The following example suggests that, in a case like this, an alternative scaling will ensure that the relevant restriction on B_1 is a zero restriction after all. Let $m_{t+1} = \log(M_{t+1}/P_t)$, where M_{t+1} is a representative household's end-of-period t holdings of money and P_t is the price level. In equilibrium, M_{t+1} must equal what is supplied by the monetary authority, so that $M_{t+1} = M_t \exp(x_t)$, where x_t is the money growth rate which is assumed, for the purpose of the illustration, to be exogenous. Then, $m_{t+1} = m_t - \log(\pi_t) + x_t$, where $\pi_t = P_t/P_{t-1}$. Suppose further that (as in Chari, Kehoe and McGrattan (1996) and Christiano, Eichenbaum and Evans (1997)) P_t is set by firms *prior* to the realization of the date t random variables and that the i^{th} equation in (2.2) is their associated Euler equation. The information set in that Euler equation excludes the current value of x_t . If m_{t+1} is the i^{th} element of z_t and x_t is the k^{th} element of θ_t , then the $(i, k)^{th}$ element of B_1 is restricted to be unity, not zero. But, this reflects that P_t is transformed with M_{t+1} . If the i^{th} variable in z_t were $\log(M_t/P_t)$ instead, then the restriction on B_1 would be a zero restriction after all.

and (2.6). We find that the feedback matrix is the zero of a particular matrix polynomial. Conditional on A , the feedforward part is the solution to a linear system of equations. After deriving these equations, I describe a strategy for solving them.

Solve (2.7) recursively to express z_{t+j} , $j = 0, 1, \dots, r-1$, as a function of z_{t-1} , s_t and ϵ_{t+k} , $k = 1, \dots, r-1$. Substituting the resulting expressions into the left side of the equality in (2.2), and taking into account $\mathcal{E}_t \epsilon_{t+k} = 0$, $k > 0$, we obtain

$$\mathcal{E}_t \left[\sum_{i=0}^r \alpha_i z_{t+r-1-i} + \sum_{i=0}^{r-1} \beta_i s_{t+r-1-i} \right] = \alpha(A) z_{t-1} + \tilde{F} s_t \quad (3.1)$$

where \tilde{F} is defined by

$$\mathcal{E}_t F s_t = \tilde{F} s_t, \quad (3.2)$$

and $F = \tilde{F}$ in the standard case. Here,

$$F = \sum_{i=0}^{r-1} [\beta_i + \bar{Q}_i B_1] P^{(r-1-i)} \quad (3.3)$$

and

$$\begin{aligned} Q_0 &\equiv \alpha_0, Q_k \equiv Q_{k-1}A + \alpha_k, k = 1, 2, \dots, r \\ \alpha(A) &\equiv \alpha_0 A^r + \alpha_1 A^{r-1} + \dots + \alpha_r \equiv Q_r \end{aligned} \quad (3.4)$$

In (3.3), \bar{Q}_i is the $n_1 \times n_1$ matrix formed from the first n_1 columns of Q_i . Thus, in addition to the eigenvalue restriction mentioned above, the A that we seek must satisfy:¹⁰

$$\alpha(A) = 0_{n_1 \times n}. \quad (3.5)$$

Given A , the $n_1 \times m$ matrix B_1 must solve the restriction:

$$\tilde{F} = 0_{n_1 \times m}. \quad (3.6)$$

Note that $\alpha(A)$ in (3.5) is an r^{th} order matrix polynomial in A . Such a polynomial will in general have many matrix roots. An important substantive question is whether any of these satisfy the eigenvalue restriction and, if so, how many. Below, I develop easy to evaluate restrictions on the α_i 's in (2.2) to answer these

¹⁰A MATLAB program, `feedback.m`, which computes A given $\alpha_0, \dots, \alpha_r$ using the procedure described in the next subsection, can be obtained from the author on request.

questions. I also show that given an arbitrary matrix A , the system of equations defined by (3.6) is linear in the non-zero components of B_1 . The necessary condition for these equations to have a solution is satisfied, since the number of undetermined elements in B_1 is equal to the number of nonzero elements in \tilde{F} . The following subsection discusses the computation of A and after that I turn to B .

3.1. Computing the Feedback Part

Since the conditions in (3.5) do not involve the second moment properties of s_t , one can abstract from the latter in computing A . In particular, I simplify the analysis in this subsection by setting $s_t \equiv 0$ for all t . Then, (2.2) reduces to $\sum_{j=0}^r \alpha_j z_{t+r-1-j} = 0$, $t = 0, 1, 2, \dots$, or, in first order difference equation form:

$$aY_{t+1} + bY_t = 0, \quad t \geq 0. \quad (3.7)$$

where Y_t is an $[(r-1)n_1 + n] \times 1$ vector:

$$Y_t = \begin{pmatrix} z_{1,t+r-2} \\ \vdots \\ z_{1,t} \\ z_{t-1} \end{pmatrix}. \quad (3.8)$$

Also, the $[(r-1)n_1 + n] \times [(r-1)n_1 + n]$ matrices a and b are defined as follows:

$$a = \begin{bmatrix} \tilde{\alpha}_0 & 0_{n_1 \times [(r-2)n_1 + n]} \\ 0_{[(r-2)n_1 + n] \times n_1} & I_{(r-2)n_1 + n} \end{bmatrix}, \quad b = \begin{bmatrix} \tilde{\alpha}_1 & \tilde{\alpha}_2 & \cdots & \tilde{\alpha}_{r-1} & \alpha_r \\ -I_{n_1} & 0_{n_1} & \cdots & 0_{n_1} & 0_{n_1 \times n} \\ 0_{n_1} & -I_{n_1} & \cdots & 0_{n_1} & 0_{n_1 \times n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0_{n \times n_1} & 0_{n \times n_1} & \cdots & b_1 & b_2 \end{bmatrix} \quad (3.9)$$

where $\tilde{\alpha}_i$ is the left n_1 columns of α_i , $i = 1, \dots, r-1$. (When $q = 0$, then $\tilde{\alpha}_i = \alpha_i$ for all i .) Also, $0_{i \times j}$ and 0_i denote the $i \times j$ and $i \times i$ dimensional matrices of zeros, respectively, and I_i denotes the i dimensional identity matrix. Finally, when $q > 0$, the $n \times n_1$ and $n \times n$ dimensional matrices b_1 and b_2 are defined as follows:

$$b_1 = \begin{bmatrix} -I_{n_1} \\ 0_{qn_1 \times n_1} \end{bmatrix}, \quad b_2 = \begin{bmatrix} 0_{n_1 \times qn_1} & 0_{n_1} \\ -I_{qn_1} & 0_{qn_1 \times n_1} \end{bmatrix},$$

and when $q = 0$:

$$b_1 = -I_{n_1}, b_2 = 0_{n_1}.$$

The vector, Y_0 , is restricted by the n initial conditions, z_{-1} . The $(r-1)n_1$ elements, $z_{1,0}, \dots, z_{1,r-2}$, are free.

A *solution* to (3.7) is a sequence, $\{Y_t; t \geq 0\}$, which satisfies the initial conditions and (3.7) at all dates. A solution is *reduced rank* if there is an $n_1(r-1) \times nr$ dimensional matrix D which satisfies a certain rank condition and $DY_t = 0$ for all $t \geq 0$. The rank condition is that the square matrix formed from the first $(r-1)n_1$ columns of D corresponding to the free variables in Y_0 be invertible. A solution is *convergent* if $Y_t \rightarrow 0$ as $t \rightarrow \infty$ for all possible initial conditions. The matrix A that we seek corresponds to a reduced rank, convergent solution.

I consider two cases, one in which the matrix a is invertible and the other in which it is not.

3.1.1. The Invertible a Case

In the first case, (3.7) implies that all solutions can be expressed as $Y_t = (-a^{-1}b)^t Y_0$, or,

$$P^{-1}Y_t = \Lambda^t P^{-1}Y_0, \quad (3.10)$$

where $P\Lambda P^{-1} = -a^{-1}b$ is the eigenvector, eigenvalue decomposition of $-a^{-1}b$. According to (3.10), the set of solutions is of dimension $n_1(r-1)$. This is because each solution, $\{Y_t, t \geq 0\}$, in the set corresponds to a different setting for the $n_1(r-1)$ free parameters in Y_0 . Suppose there are exactly $n_1(r-1)$ elements in Λ that exceed unity in absolute value, and let D be composed of the $n_1(r-1)$ rows of P^{-1} associated with the explosive elements of Λ . If D satisfies the rank condition described above, then the set of convergent solutions contains one element, the one corresponding to the Y_0 satisfying $DY_0 = 0$. That Y_0 corresponds to the unique convergent solution of (3.10). This solution is a reduced rank solution because of the easily verified fact that $\bar{p}Y_0 = 0$ implies $\bar{p}Y_t = 0$ for all $t \geq 0$ when \bar{p} is one of the rows of P^{-1} .

If the number of eigenvalues larger than one in absolute value exceeds $n_1(1-r)$, then there is no reduced rank solution satisfying convergence (there are not enough degrees of freedom in the first $n_1(r-1)$ elements of Y_0 to 'zero out' all the explosive eigenvalues in (3.10).) In this case (particularly when (2.2) is a local approximation to the Euler equation associated with a nonlinear model) the solu-

tion method developed here does not directly apply.¹¹ If the number of elements of Λ exceeding unity in absolute value is less than $n_1(r-1)$, then there may be more than one reduced rank, convergent solution (the requirement of ‘zeroing out’ the explosive roots in Λ may not exhaust the $n_1(r-1)$ degrees of freedom in Y_0 .)¹² When (2.2) represents a local approximation about a nonstochastic steady state for z_t , then this is equivalent to the finding that the nonstochastic steady state is indeterminate.

Write $DY_t = D^1 Y_t^1 + D^2 z_{t-1}$, where D^1 are the $n_1(r-1)$ first columns of D and D^2 are the remaining n columns and $Y_t = [Y_t^1, z_{t-1}]'$ is partitioned conformably.

¹¹Stokey and Lucas (1989, p. 157-158) provide an example useful for thinking about this case. Their example is a two-sector growth model in which the exact policy rule diverges in a neighborhood of the nonstochastic steady state, and converges to a two-period cycle. When (2.2) is a linear expansion about steady state, then there are only non-convergent solutions to $\alpha(A) = 0$. One of these closely approximates the divergent exact solution in the neighborhood of steady state. Still, this linear approximation is very inaccurate, since the implied trajectory for z_t explodes without bound in contrast to the exact solution which is bounded. The methods of this paper can still be applied to this example, however, by redefining z_t appropriately. See Stokey and Lucas (1989, exercise 6.7f, page 158).

¹²For example, suppose the dimension of $\pi = -a^{-1}b$ is 3×3 , and $n_1(r-1) = 2$. Also, let \tilde{p}_i denote the i^{th} row of P^{-1} , $i = 1, 2, 3$. Suppose the eigenvalues of π are distinct, and real, but that only one, the first one, is explosive. Then, D can be constructed from \tilde{p}_1 and either of \tilde{p}_2 or \tilde{p}_3 . In this case, there are two reduced rank, convergent solutions. In general, when the number of explosive eigenvalues is less than $n(r-1)$, a reduced rank, convergent solution may not exist, or it may be unique. As an illustration of the former possibility, consider

$$\pi = \begin{bmatrix} 3.1 & -0.1 & -1.7 \\ 0.8 & 0.2 & -0.5 \\ 1.9 & 0.04 & -0.9 \end{bmatrix}.$$

The eigenvalues of π are 1.92 and $0.24 \pm 0.07i$, after rounding, where $i = \sqrt{-1}$. Evidently, there is only one explosive eigenvalue. So, to assure convergence, Y_0 must be orthogonal to \tilde{p}_1 . But, Y_0 cannot also be made orthogonal to any one of \tilde{p}_2 or \tilde{p}_3 . This is because these vectors are complex. That is, $\tilde{p}_2 = \alpha + i\beta$ and $\tilde{p}_3 = \alpha - i\beta$, where α and β are real 1×3 row vectors. Then, $\tilde{p}_2 Y_0 = 0$ corresponds to the two conditions, $\alpha Y_0 = \beta Y_0 = 0$. Given the assumed 2 degrees of freedom in Y_0 and the fact that one is used up by the convergence requirement, $\tilde{p}_1 Y_0 = 0$, there are not enough degrees of freedom left to impose $\tilde{p}_i Y_0 = 0$ for $i = 2$ or 3 . To see that the number of reduced rank, convergent solutions may be unique, even when the number of eigenvalues is less than $n_1(r-1)$, consider a version of the π matrix above in which the real, explosive eigenvalue is replaced by one that is less than one in absolute value. Then, the unique convergent, reduced rank solution is the Y_0 such that $DY_0 = 0$, where the rows of D are composed of α and β .

Then, $DY_t = 0$ implies

$$Y_t^1 = -(D^1)^{-1}D^2z_{t-1}, \quad (3.11)$$

where $-(D^1)^{-1}D^2$ is an $n_1(r-1) \times n$ matrix. The matrix A_1 that we seek is composed of the bottom n_1 rows of $-(D^1)^{-1}D^2$.

3.1.2. The Non-Invertible a Case

Now consider the case when a is not invertible.¹³ The procedure I use for handling this case is based on the QZ decomposition, as implemented by Chris Sims (1989).¹⁴ For notational simplicity, let $\omega \equiv (r-1)n_1 + n$, so that a and b are $\omega \times \omega$ matrices.

The first step is to find the orthonormal matrices Q and Z , and the upper triangular matrices H_0 and H_1 with the properties:

$$QaZ = H_0, \quad QbZ = H_1. \quad (3.12)$$

The matrix H_0 is structured so that the l zeros on its diagonal are located in the lower right part of H_0 . Denote the upper $(\omega-l) \times (\omega-l)$ block of H_0 by G_0 . This matrix must be non-singular. Let the corresponding upper left $(\omega-l) \times (\omega-l)$ block in H_1 be denoted G_1 . I assume that the lower right $l \times l$ block of H_1 is nonsingular. Also, it is useful to partition Z' as follows:

$$Z' = \begin{pmatrix} L_1 \\ L_2 \end{pmatrix}, \quad (3.13)$$

where L_1 is $(\omega-l) \times \omega$ and L_2 is $l \times \omega$.

Inserting ZZ' ($= I$) before Y_{t+1} and Y_t in (3.7), defining $\gamma_t \equiv Z'Y_t$, and pre-multiplying (3.7) by Q , (3.7) becomes:

$$H_0\gamma_{t+1} + H_1\gamma_t = 0, \quad t = 0, 1, \dots \quad (3.14)$$

Partition γ_t as follows:

$$\gamma_t = \begin{pmatrix} \gamma_t^1 \\ \gamma_t^2 \end{pmatrix}, \quad (3.15)$$

¹³See example 2 in the next section, for an illustration of how this case can arise in practice.

¹⁴The MATLAB program, `feedback.m`, makes use of software for written by Chris Sims.

where γ_t^1 is $(\omega - l) \times 1$ and γ_t^2 is $l \times 1$. It is easy to verify that (3.14) implies $\gamma_t^2 = 0, t \geq 0$, i.e.,

$$L_2 Y_t = 0, t = 0, 1, \dots \quad (3.16)$$

With (3.16) imposed, the last l equations in (3.14) are redundant, so (3.14) can be written

$$G_0 \gamma_{t+1}^1 + G_1 \gamma_t^1 = 0, t = 0, 1, \dots \quad (3.17)$$

The set of solutions to this system can be expressed as $\gamma_t^1 = (-G_0^{-1}G_1)^t \gamma_0^1, t \geq 0$. or,

$$P^{-1} \gamma_t^1 = \Lambda^t P^{-1} \gamma_0^1, \quad (3.18)$$

where $P \Lambda P^{-1} = -G_0^{-1}G_1$ is the eigenvector, eigenvalue decomposition of $-G_0^{-1}G_1$. The γ_t^1 that solve (3.18) are convergent if, and only if, $\bar{p} \gamma_0^1 = 0$, where \bar{p} is composed of the rows of P^{-1} corresponding to diagonal terms in Λ that exceed 1 in absolute value. This condition is:

$$\bar{p} L_1 Y_0 = 0. \quad (3.19)$$

Recall that the number of free (i.e., endogenously determined) elements in Y_0 is $n_1(r-1)$. Equation (3.16) for $t = 0$ represents l restrictions on Y_0 , so that to pin Y_0 down uniquely, $n_1(r-1) - l$ more restrictions are needed. Thus, uniqueness requires that there be $n_1(r-1) - l$ explosive eigenvalues in Λ , i.e., that $\bar{p} L_1$ contain $n_1(r-1) - l$ rows. Then, define

$$D = \begin{bmatrix} \bar{p} L_1 \\ L_2 \end{bmatrix}. \quad (3.20)$$

The matrix A that we seek is then obtained by manipulating D in exactly the same way that was done before (see the discussion after equation (3.11).)

3.2. Computing the Feedforward Part

With the A matrix in hand, I now find the B matrix which solves (3.6) conditional on the given matrix, A . I consider two cases. In the standard case, $\mathcal{E}_t F s_t = F s_t$, so that I require $F = 0$. The following result is useful:

$$vec(A_1 A_2 A_3) = (A_3' \otimes A_1) vec(A_2) \quad (3.21)$$

where \otimes denotes the Kronecker product and $vec(\cdot)$ denotes the vectorization operator.¹⁵ Also, $vec(A + B) = vec(A) + vec(B)$. Applying these results to (3.3), I get

$$vec(F') = vec\left[\sum_{j=0}^{r-1} (P')^{r-1-j} \beta'_j\right] + \left\{\sum_{j=0}^{r-1} [\bar{Q}_j \otimes (P^{r-1-j})']\right\} vec(B'_1), \quad (3.22)$$

where $P^0 \equiv I$ and $'$ denotes the matrix transposition operator. Then, $vec(F') = 0$ implies

$$d + q\delta = 0, \quad (3.23)$$

where

$$q = \left\{\sum_{j=0}^{r-1} [\bar{Q}_j \otimes (P^{r-1-j})']\right\}, \quad d = vec\left[\sum_{j=0}^{r-1} (P')^{r-1-j} \beta'_j\right], \quad \text{and } \delta = vec(B'_1). \quad (3.24)$$

Note here that q and d are determined, given A . The solution we seek is

$$\delta = -q^{-1}d. \quad (3.25)$$

The matrix B_1 can be recovered in a straightforward way from δ .

Now consider the case in which $\mathcal{E}_t F s_t = \tilde{F} s_t \neq F s_t$. One difference between F and \tilde{F} is that the latter contains a zero in its i, j^{th} entry if the j^{th} element of s_t is excluded in Ω_{it} . The matrices F and \tilde{F} have the following linear relationship:

$$\overline{vec}(\tilde{F}') = R vec(F'). \quad (3.26)$$

Here, $\overline{vec}(\tilde{F}')$ coincides with $vec(\tilde{F}')$, except that entries corresponding to elements in \tilde{F} that are assigned a zero value by exclusion restrictions in Ω_{it} are deleted. For a simple illustration of the construction of R , see example 3 in section 4. Appendix 1 describes a general algorithm for constructing R from τ , ρ , and V_e . The matrix, V_e , is needed for this mapping in case some elements of θ_t are

¹⁵If $X = [x_1 : x_2 : \dots : x_n]$, where x_i denotes the i^{th} column of X , then

$$vec(X) \equiv \begin{bmatrix} x_1 \\ \dots \\ x_n \end{bmatrix}.$$

observed contemporaneously and others not (i.e., at least one τ_i has neither all zeros nor all ones). In this case, the elements that are not observed must be projected onto the ones that are, and this projection formula requires the covariance between the various shock innovations.

Given the simple relationship between F and \tilde{F} given by (3.26), obtaining B_1 involves a straightforward modification on the algorithm leading to (3.25). Define $\tilde{d} = Rd$, let $\tilde{\delta} = \overline{vec}(B'_1)$, and note that B_1 has zeros in the same entries as \tilde{F} . Also, let \tilde{q} denote Rq after the columns of Rq corresponding to the zero elements in $vec(B'_1)$ have been removed. Premultiplying (3.23) and taking the latter into account, we obtain, $\tilde{d} + \tilde{q}\tilde{\delta} = 0$, so that

$$\tilde{\delta} = -\tilde{q}^{-1}\tilde{d}. \tag{3.27}$$

The matrix B_1 can be recovered in a straightforward way from $\tilde{\delta}$.

4. Some Examples of The Solution Method

In this section I describe five examples which help illustrate aspects of the general algorithm described in the previous section. The first example is a basic real business cycle model in which labor is exogenously held fixed. I use this example to establish some notation, and to introduce, in the simplest possible way, the idea of the undetermined coefficient solution method. In addition, I use the example to illustrate how (2.2) could arise as an approximation to a nonlinear model. The second example endogenizes the labor decision. This change causes the matrix a discussed in section 3.1 to be non-invertible. The example is used to illustrate the strategy outlined in section 3.1.2 above for dealing with this. The third example illustrates how the solution algorithm can accommodate situations in which different decisions are based on different information sets. The example modifies the second example by assuming that the investment decision is made prior to the realization of the technology shock, while the labor decision is made afterward. The fourth example is a simple version of Kydland and Prescott (1983)'s 'Time to Build' model and illustrates the possibility that $q > 0$ in section 2. This corresponds to the case in which the vector z_t must include lagged values of the current period decision variables. My final example illustrates how the solution method can be used to solve a model with non-trivial cross-sectional heterogeneity.

4.1. Example 1: Real Business Cycle Model With Exogenous Labor

Consider a one-sector neoclassical growth model in which there is only a saving/consumption decision. A planner solves the following problem: Maximize expected utility $E_0 \sum_{t=0}^{\infty} \beta^t U(C_t)$ subject to the resource constraint, $C_t + K_{t+1} - (1 - \delta)K_t = f(K_t, \theta_t)$, where β is the discount rate, C_t is consumption, K_t is the capital stock, δ is the depreciation rate on capital, f is the production function and θ_t is a shock to technology:

$$\theta_t = \rho\theta_{t-1} + e_t, \quad e_t \sim N(0, \sigma_e^2), \quad (4.1)$$

where ρ is a scalar less than unity in absolute value. The first order condition for the capital investment decision with the resource constraint imposed to eliminate consumption is:

$$0 = E[v(K_{t+2}, K_{t+1}, K_t, \theta_{t+1}, \theta_t) | \theta_t], \quad (4.2)$$

for all $t \geq 0$, θ_t , K_t , where f_K denotes the partial derivative of f with respect to its first argument, U_c denotes the marginal utility of consumption, and

$$\begin{aligned} & v(K_{t+2}, K_{t+1}, K_t, \theta_{t+1}, \theta_t) \\ = & U_c(f(K_t, \theta_t) + (1 - \delta)K_t - K_{t+1}) \\ & - \beta U_c(f(K_{t+1}, \theta_{t+1}) + (1 - \delta)K_{t+1} - K_{t+2}) [f_K(K_{t+1}, \theta_{t+1}) + 1 - \delta]. \end{aligned}$$

The exact solution to the problem is a policy rule, $K_{t+1} = g(K_t, \theta_t)$, that satisfies equation (4.2). That is,

$$E\{v(g(g(K_t, \theta_t), \theta_{t+1}), g(K_t, \theta_t), K_t, \theta_{t+1}, \theta_t) | \theta_t\} = 0 \quad (4.3)$$

for all $K_t \geq 0$ and for all θ_t . Determining $g(\cdot)$ exactly is not feasible in general. In effect, solving for $g(\cdot)$ corresponds to solving a continuum of equations (one for each possible value of K_t and θ_t in (4.3)) in a continuum of unknowns (a value for $g(K_t, \theta_t)$ corresponding to each possible K_t and θ_t). In practice, one of at least two alternative strategies are adopted. One approximates $g(\cdot)$ with a function having a finite number of unknown parameters. The values of these parameters are determined by requiring that (4.3) (or linear combinations of it) be satisfied at a finite number of values of K_t and θ_t (see, for example, Judd (1992) or Christiano and Fisher (1997).) This is a nonlinear undetermined coefficients method. The strategy pursued in this paper exploits the observation that if v were

linear, then the exact solution is straightforward to find. This strategy replaces v by its linear first order Taylor series expansion about $K_{t+2} = K_{t+1} = K_t = K_s$ and $\theta_{t+1} = \theta_t = E\theta_t$. Here, K_s denotes the nonstochastic steady state value of K_t , i.e., the solution to $v(K_s, K_s, K_s, E\theta_t, E\theta_t) = 0$. The rationale for this approach is that v itself is often not far from linear. Since it is not *exactly* linear, however, some sort of linear approximation must be taken. The approximation is taken in the region of the nonstochastic steady state on the grounds that this is where the model variables are with high probability in the exact solution.

Let $z_{1t} = z_t = [K_{t+1} - K_s]'$, $s_t = [\theta_t - E\theta_t]'$, $P = \rho$, $m = 1$ and $\epsilon_t = e_t$. Using this notation, the linear approximation to (??) may be written in the form of (2.2):

$$E_t \{ \alpha_0 z_{t+1} + \alpha_1 z_t + \alpha_2 z_{t-1} + \beta_0 s_{t+1} + \beta_1 s_t | s_t \} = 0,$$

for all z_{t-1} and s_t . Here, $n_1 = n = 1$, $q = 0$ and $r = 2$. Also,

$$\alpha_0 = \frac{dv(K_{t+2}, K_{t+1}, K_t, \theta_{t+1}, \theta_t)}{dK_{t+2}}, \text{ for } K_{t+2} = K_{t+1} = K_t = K_s \text{ and } \theta_{t+1} = \theta_t = E\theta_t,$$

and $\alpha_1, \alpha_2, \beta_0, \beta_1$ are defined similarly. Values for the scalars A and B in

$$z_t = Az_{t-1} + Bs_t = g(z_{t-1}, s_t),$$

say, can be found that satisfy

$$E_t \{ \alpha_0 g(g(z_{t-1}, s_t), s_{t+1}) + \alpha_1 g(z_{t-1}, s_t) + \alpha_2 z_{t-1} + \beta_0 s_{t+1} + \beta_1 s_t | s_t \} = 0,$$

for all z_{t-1} and s_t . Evaluating this expression, we get the analog of (3.1):

$$\alpha(A)z_{t-1} + Fs_t + E_t\beta_0\epsilon_{t+1} = \alpha(A)z_{t-1} + Fs_t = 0.$$

Here, we have used the fact that we are in the 'standard case', $\mathcal{E}_t[X_t] = E_t[X_t]$, with $F = \tilde{F}$. Also,

$$\alpha(A) = \alpha_0 A^2 + \alpha_1 A + \alpha_2, \quad F = (\beta_0 + \alpha_0 B)P + [\beta_1 + (A\alpha_0 + \alpha_1)B].$$

To solve this, first find A that satisfies $\alpha(A) = 0$, and then solve the linear equation in B , $F = 0$, to find B . It is easily verified that there are two real values of A that solve $\alpha(A) = 0$: one is positive and less than one and the other exceeds β^{-1} (see Stokey and Lucas (1989, p. 155).) The appropriate choice for A is the smaller

of these two. This is because it is known that in the version of this model with $\sigma_\varepsilon = 0$, the exact policy function, $K' = g(K, \theta)$, cuts the 45 degree line from above at $K_t = K_s$ when $\theta_t = E\theta_t$ (see Stokey and Lucas (1989, p. 135).) Thus, with this choice of A , we can hope that the resulting linear policy rule may be a good approximation to the exact policy rule.

As I have just shown, the approximate linear solution to this model can be found by computing the zeros of a particular second order scalar polynomial and then solving a linear equation in one unknown. Clearly, the matrix algebra approach laid out in the previous section for doing this is unnecessary here. Still, it is useful to indicate how that approach applies in this example as a way of illustrating how it works.

Consider the computation of the feedback part, A , discussed in section 3.1. The system without s_t may be written in the first order difference equation form. (3.7), with the following settings for a , b , and Y_t :

$$Y_t = \begin{bmatrix} z_t \\ z_{t-1} \end{bmatrix}, \quad a = \begin{bmatrix} \alpha_0 & 0 \\ 0 & I \end{bmatrix}, \quad b = \begin{bmatrix} \alpha_1 & \alpha_2 \\ -I & 0 \end{bmatrix}.$$

Since we are in the invertible a case (see section 3.1.1), we may define:

$$P\Lambda P^{-1} = -a^{-1}b, \quad \Lambda = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix},$$

where λ_i are the eigenvalues of $-a^{-1}b$, and the columns of P are the associated eigenvectors. For convenience, the eigenvalues are ordered so that $\lambda_1 > \lambda_2$. It is readily verified by studying the second order polynomial in λ , $\det(-a^{-1}b - \lambda I)$, that the λ_i 's are just the two solutions to $\alpha(A) = 0$ discussed above. In addition,

$$P^{-1} = \begin{bmatrix} 1 & -\lambda_2 \\ 1 & -\lambda_1 \end{bmatrix}.$$

The matrix D referred to in section 3.1.1 is composed of the $n_1(r-1) = 1$ row of P^{-1} corresponding to the explosive eigenvalue, λ_1 . Thus, $D = (1, -\lambda_2)$, with $D^1 = 1$ and $D^2 = -\lambda_2$, so that the policy rule in (3.11) corresponds here to $k_{t+1} - k_s = \lambda_2(k_t - k_s)$. Since λ_2 is the smaller of the two eigenvalues, this solution coincides with the one identified above. It is trivial to verify that the procedure for computing the feedforward part, B , in section 3.2 above coincides with the single equation procedure described above, and we do not discuss this further here.

4.2. Example 2: Real Business Cycle Model with a Labor Decision

This example is used to demonstrate the possibility that the matrix a in section 3.1 is singular, thus motivating the strategy described in section 3.1.2 for dealing with this. In the example, a planner solves the following problem: Maximize expected utility $E_t \sum_{t=0}^{\infty} \beta^t U(C_t, N_t)$ subject to the resource constraint $C_t + K_{t+1} - (1 - \delta)K_t = f(K_t, N_t, \theta_t)$, where β is the discount factor, C_t is consumption, K_t is the capital stock, N_t is labor, δ is the depreciation rate on capital, f is the production function and θ_t is a technology shock which has the same form as in the previous example. The efficiency conditions for the capital investment and labor decisions with the resource condition imposed to eliminate consumption are:

$$0 = E[v_K(K_{t+2}, N_{t+1}, K_{t+1}, N_t, K_t, \theta_{t+1}, \theta_t) | \theta_t] \quad (4.4)$$

and

$$0 = v_N(K_{t+1}, N_t, K_t, \theta_t). \quad (4.5)$$

for all $t \geq 0$, and for all K_t, θ_t . Here, f_K denotes the partial derivative of f with respect to its first argument, f_N denotes the partial derivative of f with respect to its second argument, and U_c, U_N denote the partial derivatives of utility with respect to consumption and labor. Also,

$$\begin{aligned} & v_K(K_{t+2}, N_{t+1}, K_{t+1}, N_t, K_t, \theta_{t+1}, \theta_t) \\ = & U_c(f(K_t, N_t, \theta_t) + (1 - \delta)K_t - K_{t+1}, N_t) \\ & - \beta U_c(f(K_{t+1}, N_{t+1}, \theta_{t+1}) + (1 - \delta)K_{t+1} - K_{t+2}, N_{t+1}) [f_K(K_{t+1}, N_{t+1}, \theta_{t+1}) + 1 - \delta] \end{aligned}$$

and,

$$\begin{aligned} v_N(K_{t+1}, N_t, K_t, \theta_t) = & U_N(f(K_t, N_t, \theta_t) + (1 - \delta)K_t - K_{t+1}, N_t) \\ & + U_c(f(K_t, N_t, \theta_t) + (1 - \delta)K_t - K_{t+1}, N_t) f_N(K_t, N_t, \theta_t). \end{aligned}$$

Let $z_{1,t} = z_t = [K_{t+1} - K_s, N_t - N_s]'$, where K_s and N_s solve

$$v_K(K_s, N_s, K_s, N_s, K_s, E\theta_t, E\theta_t) = 0, \quad v_N(K_s, N_s, K_s, E\theta_t) = 0.$$

Also, let $s_t = \theta_t$, $P = \rho$, $n_1 = n = 2$, $q = 0$, $r = 2$, and $\epsilon_t = e_t$. After approximating v_K and v_N by their linear Taylor series expansions about steady state, the resulting linearized system can be expressed in the form of (2.2), with \mathcal{E}_t corresponding to

the ‘standard case’, i.e., $\mathcal{E}_t[X_t] = E_t X_t$. To find A in (2.7) using the method of section 3.1, we begin by setting up (3.7):

$$Y_t = \begin{bmatrix} z_t \\ z_{t-1} \end{bmatrix}, \quad a = \begin{bmatrix} \alpha_0 & 0_{2 \times 2} \\ 0_{2 \times 2} & I_2 \end{bmatrix}, \quad b = \begin{bmatrix} \alpha_1 & \alpha_2 \\ -I_2 & 0_{2 \times 2} \end{bmatrix},$$

where $0_{2 \times 2}$ is the 2 by 2-dimensional matrix of zeros and I_2 is a 2 by 2-dimensional identity matrix. Let the first and second rows of (3.7) correspond to the linearized version of equations (4.4) and (4.5), respectively. That is,

$$\alpha_0 = \begin{bmatrix} v_{K,1} & v_{K,2} \\ 0 & 0 \end{bmatrix}, \quad \alpha_1 = \begin{bmatrix} v_{K,3} & v_{K,4} \\ v_{N,1} & v_{N,2} \end{bmatrix}, \quad \alpha_2 = \begin{bmatrix} v_{K,5} & 0 \\ v_{N,3} & 0 \end{bmatrix}, \quad (4.6)$$

where $v_{K,i}$ and $v_{N,i}$ are the derivatives of v_K and v_N , respectively, with respect to their i^{th} argument, evaluated in nonstochastic steady state. The fact that a is not invertible reflects that the second row of α_0 and, hence, of a itself, is composed of zeros.¹⁶ This is why the matrix A must be computed using the method of section 3.1.2 and not of section 3.1.1.

Computation of B is straightforward. For this, we require the β 's:

$$\beta_0 = \begin{pmatrix} v_{K,6} \\ 0 \end{pmatrix}, \quad \beta_1 = \begin{pmatrix} v_{K,7} \\ v_{N,4} \end{pmatrix}. \quad (4.7)$$

The rest is a straightforward application of the methods in section 3.2.

4.3. Example 3: Real Business Cycle Model with Labor Decision and Imperfect Information

In some models, the expectation operator applied to different Euler equations is evaluated relative to different information sets. This can happen when some

¹⁶At first glance, it may appear that one way to deal with the problem of lack of invertibility is to instead define a and b as follows:

$$a = \begin{bmatrix} \alpha_0 & \alpha_1 \\ 0_{2 \times 2} & I_2 \end{bmatrix}, \quad b = \begin{bmatrix} 0_{2 \times 2} & \alpha_2 \\ -I_2 & 0_{2 \times 2} \end{bmatrix}.$$

In fact, this does not help the singularity problem. To see this, note that the second row of α_1 can be expressed as a linear combination of the rows of I_2 . But, given that the second row of α_0 is composed of zeros, this implies that the second row of a itself can be expressed as a linear combination of its third and fourth rows.

variables are determined before the realization of some or all the current period shocks, while others are determined afterward. We illustrate this possibility using a modified version of the previous example. In the modification, we assume the date t labor decision is made after, and the date t investment decision is made before, the realization of the current value of θ_t . Thus, the date t investment decision is made based on the information set $\Omega_{1t} = \{z_{t-1}, \theta_{t-1}\}$ and the date t hours decision is made based on the information set $\Omega_{2t} = \{z_{t-1}, \theta_t\}$. With this modification, we cannot define s_t as in example 2. Instead, we set $s_t = (\theta_t, \theta_{t-1})'$, $\epsilon_t = (e_t, 0)'$ and

$$P = \begin{bmatrix} \rho & 0 \\ 1 & 0 \end{bmatrix}.$$

To put this problem in the form of (2.2), the α_i 's are constructed using (4.6). The discussion of the computation of the matrix A in the previous example also applies here. The impact of the changed information sets occurs in the construction of the β_i 's and in the formulas for computing B . The β_i 's are obtained as follows:

$$\beta_0 = \begin{pmatrix} v_{K,6} & 0 \\ 0 & 0 \end{pmatrix}, \beta_1 = \begin{pmatrix} v_{K,7} & 0 \\ v_{N,4} & 0 \end{pmatrix},$$

where the $v_{K,i}$'s and $v_{N,4}$ are defined in the previous example. To get B using the computed matrix A and these β_i 's, first compute F in (3.3):

$$\begin{aligned} F &= [(\beta_0 + \alpha_0 B)P + (\beta_1 + \alpha_1 B + \alpha_0 AB)] \\ &= \begin{bmatrix} F_{11} & F_{12} \\ F_{21} & F_{22} \end{bmatrix}, \end{aligned}$$

so that,

$$\mathcal{E}_t F s_t = \mathcal{E}_t \begin{bmatrix} F_{11}\theta_t + F_{12}\theta_{t-1} \\ F_{21}\theta_t + F_{22}\theta_{t-1} \end{bmatrix} = \begin{bmatrix} 0 & F_{12} + \rho F_{11} \\ F_{21} & F_{22} \end{bmatrix} s_t = \tilde{F} s_t.$$

Then, it is readily confirmed that the matrix R in (3.26) is:

$$R = \begin{bmatrix} \rho & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

Define:

$$\tilde{d} = R \text{vec}[P' \beta'_0 + \beta'_1],$$

and \tilde{q} is the 3×3 matrix obtained by deleting the first column from the 3×4 matrix,

$$R\{\alpha_0 \otimes P' + [\alpha_0 A + \alpha_1] \otimes I\}.$$

Finally,

$$\tilde{\delta} = \overline{vec}(B') = \begin{bmatrix} B_{12} \\ B_{21} \\ B_{22} \end{bmatrix}.$$

Then, $\tilde{\delta}$ is computed from $\tilde{\delta} = -\tilde{q}^{-1}\tilde{d}$. The matrix, B , is obtained as follows:

$$B = \begin{bmatrix} 0 & \tilde{\delta}_1 \\ \tilde{\delta}_2 & \tilde{\delta}_3 \end{bmatrix},$$

where $\tilde{\delta} = (\tilde{\delta}_1, \tilde{\delta}_2, \tilde{\delta}_3)'$.

4.4. Example 4: Real Business Cycle Model with Time-to-Build Investment Technology

This example illustrates the possibility that $q > 0$ in the construction of z_t in (2.1). Consider a two period time-to-build economy, with exogenously fixed labor. This is a modified version of the economy in example 1. The modification is that now resources must be devoted for two periods, rather than just one, to augment the stock of capital. A planner maximizes $E_0 \sum_{t=0}^{\infty} \beta^t U(C_t)$, subject to the resource constraint, $C_t + I_t \leq f(K_t, \theta_t)$, where θ_t has the same distribution as in the previous examples. Also, I_t denotes investment, which is composed of resources devoted to projects initiated in the current period and resources devoted to projects initiated in the previous period. That is:

$$I_t = \phi x_t + (1 - \phi)x_{t-1}. \quad (4.8)$$

The investment technology requires that if x_t units of gross investment is to occur during period $t + 1$, i.e.,

$$K_{t+2} - (1 - \delta)K_{t+1} = x_t, \quad (4.9)$$

then resources in the amount ϕx_t must be applied in period t and $(1 - \phi)x_t$ must be applied in period $t + 1$, where $0 \leq \phi \leq 1$. In (4.9), δ is the rate of depreciation on a unit of capital. Once an investment project is initiated, its scale cannot be

expanded or contracted. As a result, x_{t-1} (hence, K_{t+1}) is a state variable at time t , in addition to K_t and θ_t . Since the date t choice variable is K_{t+2} , the policy rule is $K_{t+2} = g(K_{t+1}, K_t, \theta_t)$. This implies that $n_1 = 1$, $z_{1t} = K_{t+2} - K_s$, and $q = 1$, so that

$$z_t = \begin{bmatrix} z_{1t} \\ z_{2t} \end{bmatrix}, \quad z_{2t} = z_{1t-1}.$$

I now describe how to set up the problem in the form of (2.2). Substituting out for I_t in the resource constraint using (4.8) and (4.9), we get:

$$C_t = f(K_t, \theta_t) - (\phi_1 K_{t+2} + \phi_2 K_{t+1} + \phi_3 K_t),$$

where

$$\phi_1 = \phi, \quad \phi_2 = (1 - \phi) - \phi(1 - \delta), \quad \phi_3 = -(1 - \phi)(1 - \delta).$$

The planner's problem is:

$$\max_{\{K_{t+2}\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t U(f(K_t, \theta_t) - (\phi_1 K_{t+2} + \phi_2 K_{t+1} + \phi_3 K_t)),$$

which leads to the following Euler equation:

$$E \left\{ \phi_1 U_{c,t} + \phi_2 \beta U_{c,t+1} - \beta^2 U_{c,t+2} [f_{K,t+2} - \phi_3] | \theta_t \right\} = 0,$$

for all θ_t, K_t , where $U_{c,t}$ is the marginal utility of consumption. This Euler equation can be written

$$E \{ v(K_{t+4}, K_{t+3}, K_{t+2}, K_{t+1}, K_t, \theta_{t+2}, \theta_{t+1}, \theta_t) | \theta_t \} = 0.$$

Solve for the nonstochastic steady state by finding the K_s that satisfies

$$v(K_s, K_s, K_s, K_s, K_s, E\theta_t, E\theta_t, E\theta_t) = 0.$$

Let $r = 3$, $s_t = \theta_t$, $P = \rho$, $\epsilon_t = e_t$, $m = 1$ and the expectation operator in (2.2) corresponds to what it is in the standard case. Finally, let V_i denote the derivative of v with respect to its i^{th} argument, evaluated in nonstochastic steady state, $i = 1, \dots, 8$ so that,

$$\begin{aligned} \alpha_0 &= [V_1, 0], \quad \alpha_1 = [V_2, 0], \quad \alpha_2 = [V_3, 0], \quad \alpha_3 = [V_4, V_5], \\ \beta_0 &= V_6, \quad \beta_1 = V_7, \quad \beta_2 = V_8. \end{aligned}$$

With the problem set up in the form of (2.2), the solution strategy of the previous section can be applied to develop an approximation to the policy rule, g .

4.5. Example 5: Model with Heterogeneous Capital

With one exception, the model described here corresponds to the real business cycle model in example 2. Instead of capital being homogeneous, there exist different types of capital, each embodying different levels of technology. Capital embodying relatively low-level technology - which tends to be older capital - is scrapped as its productivity lags behind that of the ‘leading edge’ technology. The leading edge technology grows as a random walk with drift. The salvage value of scrapped capital and investment goods are used to produce new capital, which incorporates the leading edge technology. The model and basic solution strategy are taken from Campbell (1997). The allocations in the model’s competitive equilibrium solve a social planning problem. To keep the discussion brief, I focus on that problem here. For a detailed discussion of the competitive equilibrium, see Campbell (1997). A closely related model, in which the heterogeneity reflects varying productivity of workers, is presented in Merz (1996).

There is one good in this economy, which can be used for consumption or investment. Labor and capital are needed for production. Capital embodies different levels of technology. The quantity of period t capital with level of technology θ is denoted $k_t(\theta)$, where θ is an index of productivity and $\theta \in (-\infty, +\infty)$. The aggregate production function of this model economy is:

$$Y_t = N_t^\alpha \left[\int_{-\infty}^{\infty} e^\theta k_t(\theta) d\theta \right]^{1-\alpha} \quad (4.10)$$

where N_t denotes labor input and $\alpha \in (0, 1)$.

At the end of the period a fraction, δ , of capital at each technology level depreciates. The remaining capital is either scrapped, or it undergoes a random change in the level of its technology. Capital is scrapped if its level of technology is below some endogenously selected cutoff, $\bar{\theta}_t$. A unit of capital that is scrapped has salvage value s . The total amount of salvaged capital in period t is:

$$S_t = (1 - \delta)s \int_{-\infty}^{\bar{\theta}_t} k_t(\theta) d\theta. \quad (4.11)$$

Capital that is not scrapped draws another productivity level according to:

$$\theta_{t+1} \sim N(\theta_t, \sigma^2). \quad (4.12a)$$

A unit of newly constructed capital that operates in period $t + 1$ draws its level of technology from the following distribution:

$$\theta_{t+1} \sim N(\nu_t, \sigma^2), \quad (4.13a)$$

where ν_t is the leading edge technology which evolves according to:

$$\nu_t = \mu_\nu + \nu_{t-1} + \epsilon_t^\nu \text{ where } \epsilon_t^\nu \sim N(0, \sigma_\nu^2), \mu_\nu > 0. \quad (4.14)$$

Each unit of capital draws its θ independently of the others.

The distribution assumptions, (4.12a) and (4.13a), imply that the law of motion of the distribution of capital by state of technology evolves as follows:

$$k_{t+1}(\theta') = (1 - \delta) \int_{\theta_t}^{\infty} \frac{1}{\sigma} \phi\left(\frac{\theta' - \theta}{\sigma}\right) k_t(\theta) d\theta + \frac{1}{\sigma} \phi\left(\frac{\theta' - \nu_t}{\sigma}\right) I_t. \quad (4.15)$$

Here, $k_{t+1}(\theta')$ denotes the amount of capital in period $t + 1$ having a technology level θ' and ϕ is the standard normal density function. The first term on the right side of equation (4.15) is the amount of period $t + 1$ capital with technology level θ' which evolved from capital which was in place in period t . The second term is the new capital with productivity θ' created in period t . Here, I_t denotes total investment in period t , and this must satisfy the resource constraint:

$$C_t + I_t = Y_t + S_t. \quad (4.16)$$

The planner's problem is to maximize the utility of a representative agent given equations (4.10)-(4.16). The maximization problem is, therefore:

$$\max_{\{C_t\}_{t=0}^{\infty}, \{N_t\}_{t=0}^{\infty}, \{I_t\}_{t=0}^{\infty}, \{Y_t\}_{t=0}^{\infty}, \{\theta_t\}_{t=0}^{\infty}, \{S_t\}_{t=0}^{\infty}, \{k_{t+1}(\theta)\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t U(C_t, N_t) \quad (4.17)$$

subject to (4.10)-(4.16), where:

$$U(C_t, N_t) = \log(C_t) + \kappa \log(1 - N_t). \quad (4.18)$$

The strategy for approximating the solution to the model proceeds in three steps. First compute the nonstochastic steady state values of the model variables. By this I mean the state to which the system converges when $\epsilon_t^\nu \equiv 0$. I do allow

idiosyncratic uncertainty in the form of $\sigma > 0$ in (4.13a) and (4.12a). Second, linearize the various equations and first order conditions that characterize the solution about the steady state values of the variables. Third, put the linearized equations in the form of (2.2) and apply the solution procedure described in section 3.

Implementation of this computational strategy requires confronting two basic problems. First, because the model exhibits growth, there is no set of constant steady state values to which the variables tend asymptotically. This problem is solved in the usual way. I exploit the model's balanced growth property by finding a scaling of the variables such that they converge in steady state. I then approximate the policy rules governing the evolution of the scaled variables of the model. At the end, a straightforward mapping takes one from the scaled objects solved for in the computations to the unscaled objects of interest. A second problem for the computational strategy is that one of the 'variables' in the model is actually a distribution. I follow Campbell (1997) by discretizing that distribution, so that $k_t(\theta)$ viewed as a function of θ is approximated by a vector. In effect, the model corresponds to a modification of the real business cycle model of example 1, in which the capital stock is a vector.

4.5.1. The Scaled Planning Problem

I begin with a discussion of the scaling of the variables. To understand the nature of the problem that scaling is designed to address, note that in equilibrium $k_t(\theta)$ shifts weight towards higher values of θ as both the leading edge state of technology and $\bar{\theta}_t$ increase with time. In addition, $k_t(\theta)$ increases in size over time. The scaling must take into account both of these phenomena. To accommodate the right-shift in $k_t(\theta)$ and $\bar{\theta}_t$, define:

$$\tilde{\theta} \equiv \theta - \nu_{t-1}, \quad \tilde{\bar{\theta}}_t \equiv \bar{\theta}_t - \nu_{t-1} . \quad (4.19)$$

Also,

$$\begin{aligned} \tilde{k}_{t+1}(\tilde{\theta}) &\equiv \frac{k_{t+1}(\theta)}{e^{\nu_t(1-\alpha)/\alpha}}, \quad \tilde{C}_t \equiv \frac{C_t}{e^{\nu_t(1-\alpha)/\alpha}}, \\ \tilde{I}_t &\equiv \frac{I_t}{e^{\nu_t(1-\alpha)/\alpha}}, \quad \tilde{S}_t \equiv \frac{S_t}{e^{\nu_t(1-\alpha)/\alpha}}, \quad \tilde{Y}_t \equiv \frac{Y_t}{e^{\nu_t(1-\alpha)/\alpha}} . \end{aligned} \quad (4.20)$$

The scaled planner's problem can be expressed in terms of the scaled variables as:

$$\begin{aligned} \max_{\{\tilde{C}_t\}_{t=0}^{\infty}, \{N_t\}_{t=0}^{\infty}, \{\tilde{I}_t\}_{t=0}^{\infty}, \{\tilde{Y}_t\}_{t=0}^{\infty},} & E_0 \sum_{t=0}^{\infty} \beta^t U(\tilde{C}_t, N_t) \\ \{\tilde{\theta}_t\}_{t=0}^{\infty}, \{\tilde{S}_t\}_{t=0}^{\infty}, \{\tilde{k}_{t+1}(\tilde{\theta}); \tilde{\theta} \in (-\infty, \infty)\}_{t=0}^{\infty} & \end{aligned} \quad (4.21)$$

subject to:

$$\begin{aligned}
\tilde{C}_t + \tilde{I}_t &= \tilde{Y}_t + \tilde{S}_t \\
\tilde{Y}_t &= e^{-\Delta\nu_t(1-\alpha)/\alpha} N_t^\alpha \tilde{K}_t^{1-\alpha} \\
\tilde{S}_t &= (1-\delta) s e^{-\Delta\nu_t(1-\alpha)/\alpha} \int_{-\infty}^{\tilde{\theta}_t} \tilde{k}_t(\tilde{\theta}) d\tilde{\theta} \\
\tilde{k}_{t+1}(\tilde{\theta}') &= (1-\delta) e^{-\Delta\nu_t(1-\alpha)/\alpha} \int_{\tilde{\theta}_t}^{\infty} \frac{1}{\sigma} \phi\left(\frac{\tilde{\theta}' - \tilde{\theta} + \Delta\nu_t}{\sigma}\right) \tilde{k}_t(\tilde{\theta}) d\tilde{\theta} + \frac{1}{\sigma} \phi\left(\frac{\tilde{\theta}'}{\sigma}\right) \tilde{I}_t,
\end{aligned} \tag{4.22}$$

where $\Delta\nu_t \equiv \nu_t - \nu_{t-1}$ and the effective stock of capital, \tilde{K}_t , is defined as:

$$\tilde{K}_t \equiv \int_{-\infty}^{\infty} e^{\tilde{\theta}} \tilde{k}_t(\tilde{\theta}) d\tilde{\theta}. \tag{4.23}$$

In (4.22), θ' is replaced by $\tilde{\theta}' - \nu_t$, consistent with (4.19). Eliminating \tilde{C}_t , \tilde{Y}_t , and \tilde{S}_t and expressing the problem in Lagrangian form, we get:

$$\begin{aligned}
&\max_{\{N_t\}_{t=0}^{\infty}, \{\tilde{I}_t\}_{t=0}^{\infty}, \{\tilde{\theta}_t\}_{t=0}^{\infty}, \{\tilde{k}_{t+1}(\tilde{\theta}); \tilde{\theta} \in (-\infty, \infty)\}_{t=0}^{\infty}} \\
&E_0 \sum_{t=0}^{\infty} \beta^t \left\{ U(\tilde{Y}_t + \tilde{S}_t - \tilde{I}_t, N_t) + \int_{-\infty}^{\infty} \lambda_t(\tilde{\theta}') m_t(\tilde{\theta}') d\tilde{\theta}' \right\},
\end{aligned} \tag{4.24}$$

where

$$\tilde{Y}_t + \tilde{S}_t = e^{-\Delta\nu_t(1-\alpha)/\alpha} \left[N_t^\alpha \tilde{K}_t^{1-\alpha} + (1-\delta) s \int_{-\infty}^{\tilde{\theta}_t} \tilde{k}_t(\tilde{\theta}) d\tilde{\theta} \right]$$

and

$$\begin{aligned}
m_t(\tilde{\theta}') &= (1-\delta) e^{-\Delta\nu_t(1-\alpha)/\alpha} \int_{\tilde{\theta}_t}^{\infty} \frac{1}{\sigma} \phi\left(\frac{\tilde{\theta}' - \tilde{\theta} + \Delta\nu_t}{\sigma}\right) \tilde{k}_t(\tilde{\theta}) d\tilde{\theta} + \frac{1}{\sigma} \phi\left(\frac{\tilde{\theta}'}{\sigma}\right) \tilde{I}_t \\
&\quad - \tilde{k}_{t+1}(\tilde{\theta}')
\end{aligned} \tag{4.25}$$

Here, $\lambda_t(\tilde{\theta}') \geq 0$ is the Lagrange multiplier associated with each period- t constraint. From the Lagrangian in (4.24) we can obtain the necessary conditions for an optimum with respect to the variables N_t , \tilde{I}_t , $\tilde{\theta}_t$, and $\tilde{k}_t(\tilde{\theta})$ for each $\tilde{\theta} \in (-\infty, \infty)$ by direct differentiation.¹⁷

¹⁷One of these ‘variables’ is a function. For a discussion of maximization with respect to a function, see, for example, Luenberger (1969, chapter 7).

The necessary conditions with respect to N_t , \tilde{I}_t and $\tilde{\theta}_t$ are, respectively:

$$\frac{\alpha e^{-\Delta\nu_t(1-\alpha)/\alpha}}{\tilde{C}_t} \left(\frac{\tilde{K}_t}{N_t} \right)^{1-\alpha} = \frac{\kappa}{1 - N_t} \quad (4.26)$$

$$1 = \int_{-\infty}^{\infty} q_t(\tilde{\theta}') \frac{1}{\sigma} \phi \left(\frac{\tilde{\theta}'}{\sigma} \right) d\tilde{\theta}' \quad (4.27)$$

$$s = \int_{-\infty}^{\infty} q_t(\tilde{\theta}') \frac{1}{\sigma} \phi \left(\frac{\tilde{\theta}' - \tilde{\theta}_t + \Delta\nu_t}{\sigma} \right) d\tilde{\theta}' \quad (4.28)$$

where $q_t(\tilde{\theta}') \equiv \tilde{C}_t \lambda_t(\tilde{\theta}')$ is the price of end-of-period capital (after it has drawn its state of technology, $\tilde{\theta}$, for next period) in the scaled competitive equilibrium decentralization of this model (see Campbell (1997)). The first of these conditions is the same as in a standard real business cycle model and needs no elaboration. The second two are particular to this model. The condition, (4.27), equates the consumption cost of one investment good, unity, to the value of the extra new capital of all vintages that it produces. According to condition (4.28), the salvage value, s , of a unit of capital that is on the margin of being scrapped must be equal to its value in case it is not scrapped, in which case it draws a new θ .

The necessary condition with respect to $\tilde{k}_{t+1}(\tilde{\theta})$ for a particular value of $\tilde{\theta}$. $\tilde{\theta}_l \in (-\infty, \infty)$, is:

$$\begin{aligned} \beta E_t \frac{e^{-\Delta\nu_{t+1}(1-\alpha)/\alpha}}{\tilde{C}_{t+1}} & \left\{ (1-\alpha) e^{\tilde{\theta}_l} \left(\frac{\tilde{K}_{t+1}}{N_{t+1}} \right)^{-\alpha} + (1-\delta) s \cdot 1\{\tilde{\theta}_l < \tilde{\theta}_{t+1}\} \right. \\ & \left. + (1-\delta) \cdot 1\{\tilde{\theta}_l \geq \tilde{\theta}_{t+1}\} \int_{-\infty}^{\infty} q_{t+1}(\tilde{\theta}') \frac{1}{\sigma} \phi \left(\frac{\tilde{\theta}' - \tilde{\theta}_l + \Delta\nu_{t+1}}{\sigma} \right) d\tilde{\theta}' \right\} \\ & = \frac{1}{\tilde{C}_t} q_t(\tilde{\theta}_l), \end{aligned} \quad (4.29)$$

where $1\{\cdot\}$ is the indicator function and is defined as follows:

$$1\{x\} = \begin{cases} 1 & \text{if } x \text{ is true} \\ 0 & \text{otherwise} \end{cases} \quad (4.30)$$

The first order condition in (4.29) corresponds to the intertemporal Euler equation in the standard real business cycle model. The term on the right of the equality is the value, expressed in utility terms, of a marginal unit of capital having technology level $\tilde{\theta}_l$ at the end of period t . This valuation occurs after period t units of

capital that survive depreciation and scrapping have drawn their period $t+1$ value of θ . The term on the left of the equality is the payoff, in discounted utility terms, from that marginal unit of capital. The first term is the period $t+1$ marginal product of that capital, and the second and third terms correspond to the end of period $t+1$ value of that unit of capital. The first of these two corresponds to the case in which $\tilde{\theta}_t$ falls below next period's scrapping cutoff, in which case the value of marginal $\tilde{k}_{t+1}(\tilde{\theta}_t)$ is just its scrap value after depreciation. The second term corresponds to the case in which $\tilde{\theta}_t$ lies above next period's scrapping cutoff. In that case, the undepreciated part of a unit of $\tilde{k}_{t+1}(\tilde{\theta}_t)$ is valued at the new value of $\tilde{\theta}$ that it will draw.

4.5.2. Model Steady States

To solve for the model's steady state, I drop time subscripts on the variables in equations (4.25) with $m_t(\tilde{\theta}^l) = 0$ and (4.26)-(4.29), and approximate the integrals with a quadrature formula. In particular, the integrals are approximated by a weighted sum of the integrand evaluated at the following M abscissas:

$$\tilde{\theta} \in \{\tilde{\theta}_1, \tilde{\theta}_2, \dots, \tilde{\theta}_M\}.$$

These same abscissas are used for each integral, regardless of the range of integration.¹⁸

I approximate \tilde{K} in (4.23) as follows:

$$\tilde{K} = \sum_{j=1}^M w_j e^{\tilde{\theta}_j} \tilde{k}_j \quad (4.31)$$

where w_j is the quadrature weight and $\tilde{k}_j \equiv \tilde{k}(\tilde{\theta}_j)$. Similarly, the resource con-

¹⁸Specifically, consider the integral, $\int_{-\infty}^{\infty} g(\tilde{\theta}) d\tilde{\theta}$. I first truncate the range of integration to $\tilde{\theta} \in (\tilde{\theta}^l, \tilde{\theta}^u)$. The abscissas, $\tilde{\theta}_0, \tilde{\theta}_1, \tilde{\theta}_2, \dots, \tilde{\theta}_M$, are uniformly distributed over the interval, $(\tilde{\theta}^l, \tilde{\theta}^u)$. Thus, with $\tilde{u}_j = (j - M/2)/(M/2)$, $j = 0, \dots, M$ I set $\tilde{\theta}_j = \tilde{\theta}^l + 0.5(\tilde{\theta}^u - \tilde{\theta}^l)(\tilde{u}_j + 1)$, $j = 0, \dots, M$. Then, the integral is approximated by the weighted sum, $\sum_{i=1}^M w_j g(\tilde{\theta}_i)$, where $w_j = (\tilde{\theta}^u - \tilde{\theta}^l)/M$. In (4.25), the lower bound of the range of integration is truncated. I accommodate this by using a weight, v_j , that is the product of w_j and the appropriately constructed indicator function. I accommodate integrals in which the upper bound of the range of integration is truncated in a similar way. I refer to the weights used for this by u_j .

straint and equations (4.26), (4.27) and (4.28) yield in steady state:

$$\begin{aligned}
\tilde{C} &= e^{-\mu\nu(1-\alpha)/\alpha} \left[N^\alpha \tilde{K}^{1-\alpha} + (1-\delta)s \sum_{j=1}^M u_j \tilde{k}_j \right] - \tilde{I} \\
\frac{\alpha e^{-\mu\nu(1-\alpha)/\alpha}}{\tilde{C}} \left(\frac{\tilde{K}}{N} \right)^{1-\alpha} &= \begin{cases} \kappa & \text{for Hansen utility} \\ \frac{\kappa}{1-N} & \text{for log-log utility} \end{cases} \\
1 &= \sum_{j=1}^M w_j \beta e^{-\mu\nu(1-\alpha)/\alpha} q_j^0 \frac{1}{\sigma} \phi \left(\frac{\tilde{\theta}_j}{\sigma} \right) \\
s &= \sum_{j=1}^M w_j \beta e^{-\mu\nu(1-\alpha)/\alpha} q_j^0 \frac{1}{\sigma} \phi \left(\frac{\tilde{\theta}_j - \tilde{\theta} + \mu\nu}{\sigma} \right).
\end{aligned} \tag{4.32}$$

Here, w_j and u_j are the quadrature weights and q_j^0 is defined as follows:

$$q_j^0 \equiv \frac{q(\tilde{\theta}_j)}{\beta} e^{\mu\nu(1-\alpha)/\alpha} \tag{4.33}$$

Equation (4.29) in non-stochastic steady state becomes:

$$\begin{aligned}
q_l^0 &= (1-\alpha) e^{\tilde{\theta}_l} \left(\frac{\tilde{K}}{N} \right)^{-\alpha} + (1-\delta)s \cdot \mathbf{1}\{\tilde{\theta}_l < \tilde{\theta}\} \\
&\quad + (1-\delta) \cdot \mathbf{1}\{\tilde{\theta}_l \geq \tilde{\theta}\} \sum_{j=1}^M w_j q_j^0 \beta e^{-\mu\nu(1-\alpha)/\alpha} \frac{1}{\sigma} \phi \left(\frac{\tilde{\theta}_j - \tilde{\theta}_l + \mu\nu}{\sigma} \right).
\end{aligned} \tag{4.34}$$

Finally, our approximation to the scaled, steady state law of motion of capital is:

$$\tilde{k}_l = (1-\delta) e^{\mu\nu(1-\alpha)/\alpha} \sum_{j=1}^M v_j \frac{1}{\sigma} \phi \left(\frac{\tilde{\theta}_l - \tilde{\theta}_j + \mu\nu}{\sigma} \right) \tilde{k}_j + \frac{1}{\sigma} \phi \left(\frac{\tilde{\theta}_l}{\sigma} \right) \tilde{I} \tag{4.35}$$

where v_j are the quadrature weights. Note that equations (4.34) and (4.35) must hold for every $l \in \{1, \dots, M\}$ and, therefore, constitute a set of M equations each.

Solving for the steady state involves solving for the $2M + 6$ unknowns:

$$\{q_l^0\}_{l=1}^{l=M}, \{\tilde{k}_l\}_{l=1}^{l=M}, \tilde{K}, \tilde{\theta}, \tilde{C}, \tilde{I}, \tilde{Y}, \tilde{S}$$

and the value of the parameter κ in the utility function to match an empirically plausible value of N .

The first step in computing our approximation to the steady state finds $\{q_l^0\}_{l=1}^{l=M}$, \tilde{K} and $\tilde{\theta}$ using the M equations in (4.34) and the last two equations in (4.32). A simple procedure to do this exploits the fact that, for a given value of $\tilde{\theta}$, equations

(4.34) and the third equation in (4.32) form a linear system of $M + 1$ equations in the $M + 1$ unknowns, $\{q_l^0\}_{l=1}^M$ and $(\tilde{K}/N)^{-\alpha}$. The procedure then assumes a value of $\tilde{\theta}$, solves the linear system for $\{q_l^0\}_{l=1}^M$ and $(\tilde{K}/N)^{-\alpha}$ and then checks if the last equation in (4.32) is satisfied. If it is satisfied, then a solution has been found; if not, one tries a different value of $\tilde{\theta}$. In effect, $\tilde{\theta}$ and $\{q_l^0\}_{l=1}^M$ and $(\tilde{K}/N)^{-\alpha}$ are found by solving a nonlinear function in $\tilde{\theta}$ alone.

The next step solves for $\{\tilde{k}_l\}_{l=1}^M$ and \tilde{I} using the pre-assigned value of N , and the linear system of equations consisting of the M equations in (4.35) and equation (4.31). I solve for \tilde{C} and for κ from (4.32). Finally, one can solve for \tilde{Y} and \tilde{S} from the discrete version of (4.22):

$$\begin{aligned}\tilde{Y} &= e^{-\mu\nu(1-\alpha)/\alpha} N^\alpha \tilde{K}^{1-\alpha} \\ \tilde{S} &= (1 - \delta) e^{-\mu\nu(1-\alpha)/\alpha} s \sum_{j=1}^M u_j \tilde{k}_j\end{aligned}$$

4.5.3. Dynamic Model Solution

To approximate the dynamic solution, I linearize the equations that characterize the model solution about the steady state that was just computed. I adopt the same quadrature approximation for the integrals in these equations as was done in the steady state calculations. In particular, they involve the fixed set of abscissas, $\{\tilde{\theta}_1, \tilde{\theta}_2, \dots, \tilde{\theta}_M\}$. Define the following functions:

$$\begin{aligned}\tilde{K}_t &= \sum_{j=1}^M w_j e^{\tilde{\theta}_j} \tilde{k}_t(\tilde{\theta}_j) \equiv \tilde{K}(\tilde{k}_t(\tilde{\theta}_1) \dots \tilde{k}_t(\tilde{\theta}_M)) \\ \tilde{C}_t &= \begin{cases} \frac{\alpha e^{-\Delta\nu_t(1-\alpha)/\alpha}}{\kappa} \left(\frac{\tilde{K}_t}{N_t}\right)^{1-\alpha} & \text{for Hansen utility} \\ \frac{\alpha e^{-\Delta\nu_t(1-\alpha)/\alpha} (1-N_t)}{\kappa} \left(\frac{\tilde{K}_t}{N_t}\right)^{1-\alpha} & \text{for log-log utility} \end{cases} \equiv \tilde{C}(\tilde{k}_t(\tilde{\theta}_1) \dots \tilde{k}_t(\tilde{\theta}_M), N_t, \Delta\nu_t) \\ \tilde{I}_t &= N_t^\alpha \tilde{K}_t^{1-\alpha} + (1 - \delta) s \sum_{j=1}^M v_j(\tilde{\theta}_t) \tilde{k}_t(\tilde{\theta}_j) - \tilde{C}_t \equiv \tilde{I}(\tilde{k}_t(\tilde{\theta}_1) \dots \tilde{k}_t(\tilde{\theta}_M), N_t, \tilde{\theta}_t, \Delta\nu_t)\end{aligned}$$

Here,

$$v_j(\tilde{\theta}_t) = 1\{\tilde{\theta}_j \leq \tilde{\theta}_t\} \times (\tilde{\theta}^u - \tilde{\theta}^l)/M,$$

and $\tilde{\theta}^u$, $\tilde{\theta}^l$ are upper and lower limits of integration which replace $+\infty$ and $-\infty$. These equations are used to eliminate \tilde{K}_t , \tilde{C}_t , and \tilde{I}_t in what follows. For example, the approximation to the law of motion of capital in equation (4.22) is:

$$\tilde{k}_{t+1}(\tilde{\theta}_l) = (1 - \delta)e^{-\Delta\nu_t(1-\alpha)/\alpha} \sum_{j=1}^M u_j(\tilde{\theta}_t) \frac{1}{\sigma} \phi\left(\frac{\tilde{\theta}_l - \tilde{\theta}_j + \Delta\nu_t}{\sigma}\right) \tilde{k}_t(\tilde{\theta}_j) + \frac{1}{\sigma} \phi\left(\frac{\tilde{\theta}_l}{\sigma}\right) \tilde{I}_t,$$

for $l \in \{1, \dots, M\}$ or,

$$V_1(\tilde{k}_{t+1}, \tilde{k}_t, N_t, \tilde{\theta}_t, \Delta\nu_t) = 0_{M \times 1},$$

where

$$\tilde{k}_{t+1} \equiv [\tilde{k}_{t+1}(\tilde{\theta}_1) \dots \tilde{k}_{t+1}(\tilde{\theta}_M)]',$$

and

$$u_j(\tilde{\theta}_t) = 1\{\tilde{\theta}_j \geq \tilde{\theta}_t\} \times (\tilde{\theta}^u - \tilde{\theta}^l)/M, \quad j = 1, \dots, M.$$

Similarly, the approximations of equations (4.27) and (4.28) are, respectively:

$$1 - \sum_{j=1}^M w_j q_t(\tilde{\theta}_j) \frac{1}{\sigma} \phi\left(\frac{\tilde{\theta}_j + \Delta\nu_t}{\sigma}\right) = 0,$$

or

$$V_2(q_t, \Delta\nu_t) = 0 \tag{4.36}$$

and,

$$s - \sum_{j=1}^M w_j q_t(\tilde{\theta}_j) \frac{1}{\sigma} \phi\left(\frac{\tilde{\theta}_j - \tilde{\theta}_t + \Delta\nu_t}{\sigma}\right) = 0$$

or,

$$V_3(q_t, \tilde{\theta}_t, \Delta\nu_t) = 0, \tag{4.37}$$

where

$$q_t = [q_t(\tilde{\theta}_1) \dots q_t(\tilde{\theta}_M)]'.$$

Finally, the discrete version of equation (4.29) is:

$$\begin{aligned} \frac{1}{\tilde{C}_t} q_t(\tilde{\theta}_l) = E_t \frac{\beta e^{-\Delta\nu_{t+1}(1-\alpha)/\alpha}}{\tilde{C}_{t+1}} & \left\{ (1 - \alpha) e^{\tilde{\theta}_l} \left(\frac{\tilde{K}_{t+1}}{N_{t+1}}\right)^{-\alpha} + (1 - \delta) s \cdot 1\{\tilde{\theta}_l < \tilde{\theta}_{t+1}\} \right. \\ & \left. + (1 - \delta) \cdot 1\{\tilde{\theta}_l \geq \tilde{\theta}_{t+1}\} \sum_{j=1}^M w_j q_{t+1}(\tilde{\theta}_j) \frac{1}{\sigma} \phi\left(\frac{\tilde{\theta}_j - \tilde{\theta}_l + \Delta\nu_{t+1}}{\sigma}\right) \right\}, \end{aligned} \tag{4.38}$$

for $l = 1, \dots, M$, or,

$$E_t V_4(\bar{k}_t, \bar{k}_{t+1}, q_t, q_{t+1}, N_t, N_{t+1}, \bar{\theta}_t, \bar{\theta}_{t+1}, \Delta\nu_t, \Delta\nu_{t+1}) = 0_{M \times 1}. \quad (4.39)$$

To apply the solution method of section 3, it is convenient to define:

$$\hat{z}_t \equiv \begin{bmatrix} \hat{k}_t \\ \hat{q}_t \\ \hat{N}_t \\ \bar{\theta}_t \end{bmatrix} \quad \text{where } \hat{k}_t \equiv \bar{k}_t - k^s \text{ and } \hat{q}_t \equiv q_t - q^s,$$

where k^s and q^s correspond to the steady states computed in the previous subsection. Then, one needs to linearize the $2M + 2$ equations $V_1(\cdot)$, $V_2(\cdot)$, $V_3(\cdot)$, and $V_4(\cdot)$ around the steady state computed above. We can now form a system of $2M + 2$ equations of the form:

$$\mathcal{E}_t [\alpha_0 \hat{z}_{t+1} + \alpha_1 \hat{z}_t + \alpha_2 \hat{z}_{t-1} + \beta_0 \Delta\nu_t + \beta_1 \Delta\nu_{t+1}] = 0,$$

where $\mathcal{E}_t [X_t] = [X'_{1t}, E_t X'_{2t}]'$ and X_{2t} corresponds to the last M equations in the previous expression. Setting the parameters $n = n_1 = 2M + 2$, $q = 0$, $r = 2$ and $m = 1$ we can use the solution methods in section 3 to solve the model.

5. Second Moment Properties and Impulse Response Functions.

The preceding sections discussed the computation of the solution, (2.7), to a system of expectational difference equations. In practice, this solution is used for two purposes, the computation of impulse response functions and of the second moment properties of a model. I briefly discuss these two issues here.

Suppose the variables of interest in the analysis include not just z_t , but also another set, x_t . Suppose that, after linearization, the latter are related to the former by the relation, $x_t = Gz_t$. The variables of interest are y_t , where

$$y_t = \begin{bmatrix} z_t \\ x_t \end{bmatrix}.$$

The impulse response functions represent the response, over time, of the elements of y_t to a pulse in one of the elements in ϵ_t in (2.4). That is, let one element in ϵ_t

be unity and the rest zero. The impulse response function, y_0, y_1, y_2, \dots is obtained by solving $s_0 = \epsilon_0$, $s_t = P^t s_0$ for $t > 0$ and $z_0 = B\epsilon_0$, $z_t = Az_{t-1} + Bs_t$, $x_t = z_t$ for $t > 0$.

There are two ways to compute second moments. One works in the time domain, and another, described in Christiano and Eichenbaum (1990, p. 50), works in the frequency domain. The time domain approach is a modification on the method described above for computing impulse response functions. Draw, from a random number generator, a sequence, ϵ_t for $t = 0, \dots, T$. Then, compute s_t , for $t = 0, \dots, T$, using (2.4) and $s_{-1} = 0$. Sequences, $z_t, x_t, t = 0, \dots, T$, can be computed using (2.7), $z_{-1} = 0$ and $x_t = Gz_t$. It is possible that the second moments of interest pertain to y_t after it has been transformed in some possibly nonlinear way. A transformation which is often used in practice is the Hodrick-Prescott filter, as described in Cooley and Prescott (1995) or Prescott (1986). The second moment properties of interest could be computed from the resulting transformed data. If T is very large, then the resulting second moments correspond to the population second moments implied by the model. One might instead be interested in the small sample second moments and choose a smaller value of T , say the value that corresponds to the sample length available in a typical data set. In this case, the second moments described will exhibit Monte Carlo sampling variation. The standard way of dealing with this repeats the calculations many times with different Monte Carlo draws of the ϵ_t 's, and reports the average, across different Monte Carlo draws, of the second moment statistics. In addition, some measure of the variation across Monte Carlo draws is also reported in practice.

The frequency domain approach to computing the population (i.e., $T = \infty$) second moments of a model proceeds as follows. Let the representation of y_t in terms of current and past ϵ_t 's be as follows:

$$y_t = G(L)\epsilon_t,$$

where L denotes the lag operator, $L\epsilon_t \equiv \epsilon_{t-1}$, and¹⁹

$$G(L) = \begin{bmatrix} I \\ G \end{bmatrix} (I - AL)^{-1} B (I - PL)^{-1} \epsilon_t.$$

The spectral density of y_t at frequency $\omega \in (-\pi, \pi)$, $S_y(\omega)$, is:

$$S_y(\omega) = G(e^{-i\omega}) V_\epsilon G(e^{i\omega})',$$

¹⁹To see how this equation is derived, note that (2.4) implies $(I - PL)s_t = \epsilon_t$. or, $s_t = (I - PL)^{-1}\epsilon_t$. Similarly, (2.7) implies $z_t = (I - AL)^{-1}Bs_t$.

where V_ϵ is the variance-covariance matrix of ϵ_t , and i is the complex number, $\sqrt{-1}$ (see Sargent (1987, ch.11, sec.6). If the moments of interest are a transformation of y_t , then it is the spectrum of this transformed process that is of interest. If in addition the transformation is linear, i.e., has the following representation:

$$\tilde{y}_t = g(L)y_t = \sum_{k=-\infty}^{\infty} g_k y_{t-k},$$

then spectrum of the transformed series is trivial to compute.²⁰ Sargent (1987, ch. 11) shows that the spectrum of \tilde{y}_t has the following form:

$$S_{\tilde{y}}(\omega) = g(e^{-i\omega})g(e^{i\omega})S_y(\omega), \text{ for } \omega \in (-\pi, \pi),$$

with $S_{\tilde{y}}(\omega) \equiv S_y(\omega)$ when it is the untransformed data that are of interest.

Let the population covariance function of \tilde{y}_t be denoted by

$$C(\tau) = E\tilde{y}_t\tilde{y}'_{t-\tau}, \quad \tau = 0, \pm 1, \pm 2, \dots$$

Then,

$$\begin{aligned} C(\tau) &= \frac{1}{2\pi} \int_{-\pi}^{\pi} S_{\tilde{y}}(\omega) e^{i\omega\tau} d\omega \\ &= \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{k=1}^N S_{\tilde{y}}(\omega_k) e^{i\omega_k\tau}, \end{aligned}$$

where $\omega_k = 2\pi \left(\frac{k}{N} - \frac{1}{2} \right)$ for $k = 1, \dots, N$ (see Sargent (1987, ch. 11, equation (20)).) The second equality reflects that we interpret the integral after the first equality as a Riemann-Stieltjes sum. In practice, the above sum converges for low values of N .²¹ The ease with which $S_{\tilde{y}}(\omega_k)$ can be computed and the above sum evaluated explains why the frequency domain approach to computing $C(\tau)$ is often used in practice.

²⁰See King and Rebelo (1993) for a derivation of $g(L)$ when the filter is the Hodrick-Prescott filter. See Sargent (1987, ch. 11) for other linear $g(L)$ functions of interest.

²¹In practice, the evaluation of the finite sum can be simplified by taking into account the symmetry properties of $e^{i\omega}$.

6. Conclusion

I have described a general approach to solving linearized rational expectations models. The strategy involves two steps. The first step solves for the feedback part of the solution by finding the zero of a matrix polynomial. The second step solves a linear system of equations to obtain the feedforward part of the solution. A simple strategy for computing impulse response functions and second moment properties was then outlined.

7. Appendix 1: Computation of the R Matrix

A feature of the algorithm described here is that information sets can vary across individual equations in the system of expectational difference equations, (2.2). The computational strategy requires the construction of a particular matrix, R , for use in (3.26). Example 3 illustrates how this matrix can easily be constructed in a simple example, by working out the relationship between two vectorized matrices. However, constructing R using this informal strategy is tedious in more complicated models. In this appendix I provide a general algorithm for constructing R .

A basic input of the algorithm is a specification of which elements in the $m_\theta \times 1$ dimensional column vector of shocks, θ_t , are observed contemporaneously, and which are excluded, in the information set, Ω_{it} , associated with the i^{th} expectational difference equation in (2.2), $i = 1, \dots, n_1$. This information is summarized in the $m_\theta \times n_1$ matrix τ , where the i^{th} column vector, τ_i , has a 1 in locations corresponding to elements of θ_t which are included, and 0's corresponding to elements of θ_t which are excluded from Ω_{it} . Let the number of 1's in τ_i be denoted by m_i . The purpose of this appendix is to provide a matrix representation of the mapping from τ, ρ, V_e to the $(n_1 m_\theta + \sum_{i=1}^{n_1} m_i) \times n_1 m$ matrix, R .

Let R_i denote the $m_i \times m_\theta$ matrix formed by deleting from the $m_\theta \times m_\theta$ identity matrix the rows corresponding to the entries in τ_i which contain a zero. Then, the components of θ_t that are observed contemporaneously in the i^{th} equation of (2.2) are given by $R_i \theta_t$. We now compute the projection of θ_t onto $R_i \theta_t$ and θ_{t-1} :

$$P[\theta_t | R_i \theta_t, \theta_{t-1}] = a_i R_i \theta_t + a_{i\theta} \theta_{t-1}. \quad (7.1)$$

$(m_\theta \times 1)$

We can distinguish three cases:

$$[a_i, a_{i\theta}] = \begin{cases} [I_{m_\theta}, 0_{m_\theta}] & \text{if } m_i = m_\theta \\ [0_{m_\theta}, \rho] & \text{if } m_i = 0 \\ \phi\Phi^{-1} & \text{if } 0 < m_i < m_\theta, \end{cases} \quad (7.2)$$

where I_{m_θ} and 0_{m_θ} denote the $m_\theta \times m_\theta$ identity and zero matrices. The third case represents the solution to $[a_i, a_{i\theta}]\Phi = \phi$, which correspond to the condition that the projection error, $\theta_t - P[\theta_t | R_i\theta_t, \theta_{t-1}]$, be orthogonal to $\theta'_t R'_i$ and θ'_{t-1} . Here, Φ is the following $(m_i + m_\theta) \times (m_i + m_\theta)$ matrix:

$$\Phi = \begin{bmatrix} R_i C R'_i & R_i \rho C \\ C' \rho' R'_i & C \end{bmatrix}, \quad C = E\theta_t \theta'_t = \sum_{i=0}^{\infty} \rho^i V_e (\rho')^i,$$

and ρC corresponds to $E\theta_t \theta'_{t-1}$. Also, ϕ is the $m_\theta \times (m_i + m_\theta)$ matrix:

$$\phi = [C R'_i, \rho C].$$

Write F in (3.3) as follows:

$$F = \begin{bmatrix} F_1 & \vdots & F_2 \end{bmatrix}, \quad F_i = \begin{bmatrix} F_{1,i} \\ \vdots \\ F_{n_1,i} \end{bmatrix}, \quad i = 1, 2,$$

$(n_1 \times m) \quad (n_1 \times m_\theta) \quad (n_1 \times m_\theta) \quad (1 \times m_\theta) \quad (1 \times m_\theta)$

so that,

$$\mathcal{E}_t F s_t = \mathcal{E}_t [F_1 \theta_t + F_2 \theta_{t-1}] = \begin{bmatrix} F_{1,1} a_1 R_1 \theta_t + F_{1,1} a_{1\theta} \theta_{t-1} & F_{1,2} \theta_{t-1} \\ \vdots & \vdots \\ F_{n_1,1} a_{n_1} R_{n_1} \theta_t + F_{n_1,1} a_{n_1, \theta} \theta_{t-1} & F_{n_1,2} \theta_{t-1} \end{bmatrix} = \tilde{F} s_t,$$

where

$$\tilde{F} = \begin{bmatrix} F_{1,1} a_1 R_1 & F_{1,1} a_{1\theta} + F_{1,2} \\ \vdots & \vdots \\ F_{n_1,1} a_{n_1} R_{n_1} & F_{n_1,2} a_{n_1, \theta} + F_{n_1,2} \end{bmatrix}.$$

Now,

$$\tilde{F}' = \begin{bmatrix} (a_1 R_1)' F'_{1,1} & (a_2 R_2)' F'_{2,1} & \cdots & (a_{n_1} R_{n_1})' F'_{n_1,1} \\ a'_{1\theta} F'_{1,1} + F'_{1,2} & a'_{2\theta} F'_{2,1} + F'_{2,2} & \cdots & a'_{n_1\theta} F'_{n_1,1} + F'_{n_1,2} \end{bmatrix},$$

so that

$$\begin{aligned}
\text{vec}(\tilde{F}') &= \begin{bmatrix} (a_1 R_1)' F'_{1,1} \\ a'_{1\theta} F'_{1,1} + F'_{1,2} \\ (a_2 R_2)' F'_{2,1} \\ a'_{2\theta} F'_{2,1} + F'_{2,2} \\ \vdots \\ (a_{n_1} R_{n_1})' F'_{n_1,1} \\ a'_{n_1\theta} F'_{n_1,1} + F'_{n_1,2} \end{bmatrix} \\
&= \begin{bmatrix} R'_1(a'_1 F'_{1,1}) & 0 & 0 & 0 & \cdots & 0 & 0 \\ a'_{1\theta} & I & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & R'_2(a'_2 F'_{2,1}) & 0 & \cdots & 0 & 0 \\ 0 & 0 & a'_{2\theta} & I & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & R'_2(a'_2 F'_{2,1}) & 0 \\ 0 & 0 & 0 & 0 & \cdots & a'_{n_1\theta} & I \end{bmatrix} \text{vec}(F') \\
&= \tilde{R} \text{vec}(F'),
\end{aligned}$$

say, where \tilde{R} is $n_1 m \times n_1 m$. Note that the rows of R'_i which correspond to the zero entries of τ_i are composed entirely of zeros. It follows that the rows of $R'_i(a'_i F'_{i,1})$ which correspond to the zero entries of τ_i are zero too. The matrix R is just \tilde{R} with these rows deleted. This matrix satisfies equation (3.26).

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