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THE LINEAR QUADRATIC ADJUSTMENT COST MODEL AND THE DEMAND FOR LABOUR

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SUMMARY

In this paper we demonstrate a new way of testing the linear quadratic adjustment cost (LQAC) model under rational expectations. We illustrate how the parameter restrictions arising from this model can be formally specified and we use these restrictions to extent the technique of Campbell and Shiller (1987) to a wider class of models based on present value relations. Potentially the demand for labour is an area in which the LQAC model can find applicability in practice and subsequently we analyse sectoral labour demand in Danish manufacturing. We find, however, that for our data set the quadratic adjustment cost model under rational expectations can be rejected.

1. INTRODUCTION

Linear quadratic adjustment cost (LQAC) models under rational expectations have been analysed in several papers including Sargent (1978), Kennan (1979), Nickell (1985), Dolado *et al.* (1991), and Gregory *et al.* (1993). Kennan and Sargent both analyse labour demand but many other kinds of models in economics fit into this set-up, see e.g. Cuthbertson (1988), Cuthbertson and Taylor (1987, 1990) and Domowitz and Hakkio (1990) for models of money demand, and Rotemberg (1982), Cuthbertson (1986), and Price (1992) for models of price adjustment. The model is based on the assumption that economic agents determine a control variable so as to minimize the present discounted value of all future squared deviations from a conjectured long-run target. However, since changes in the control variable will be penalized as well, immediate adjustment towards the steady-state level will be non-optimal.

The basic set-up of the model analysed in the present paper is similar to that of Kennan (1979) in his analysis of labour demand. However, unlike Kennan, who assumed variables to be trend stationary, we take into account the possibility of stochastic nonstationarities of the data in terms of integration and cointegration (see Engle and Granger, 1987). Provided that there is cointegration among the variables that are conjectured to constitute the desired steady state, Dolado *et al.* (1991) emphasize that estimation becomes especially attractive as the long-run parameters and the adjustment coefficients can be estimated separately due to the error-correction representation of cointegrated systems. Hence estimation can proceed in reverse order to Kennan's (1979) approach. In this paper we present an alternative method of testing LQAC models under rational expectations. The technique that we suggest is a straightforward generalization of the Campbell and Shiller (1987) method for testing rational expectations

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restrictions in present value models, and hence we extend their analysis to a potentially wider range of problems.

The plan of the paper is the following. In Section 2 the LQAC model is briefly reviewed and we formulate the solution to the optimization problem in a way that facilitates the generalization of Campbell and Shiller's present value model to account for adjustment costs. An essential feature of the Campbell and Shiller method is that it builds on an *exact* linear rational expectations model, i.e. a model with no error term. In Section 3 we show how the exact LQAC model leads to *linear* cross-equation restrictions on a VAR model written in a particular way. The restrictions of the VAR can also be formulated as a single-equation orthogonality condition. It is also shown how the LQAC model can be calibrated by the estimated parameters such that an empirical fit of the model can be achieved in accordance with Campbell and Shiller's suggestions. Obtaining a fit of the model even when the model restrictions are formally rejected is of interest, since it enables us to measure how large the deviations are from the exact theoretical model; i.e. it becomes possible to establish whether formal rejection of the model is due to fundamental discrepancies from the theoretical model *or* whether rejection follows economically less important factors. We complete the paper by applying the derived techniques to an intertemporal model of quarterly labour demand in Danish manufacturing using disaggregated data, and based on this data set we find that there is little content to the theoretical model.

2. THE MODEL

Assume that an economic agent chooses a sequence $\{l_{t+j}\}_{j=0}^{\infty}$ of an economic control variable in order to minimize the expectation of the intertemporal loss function[1]

$$L_t = \sum_{j=0}^{\infty} \beta^j [\theta(l_{t+j} - l_{t+j}^*)^2 + (l_{t+j} - l_{t+j-1})^2] \tag{1}$$

conditional on information available at time t. β is the discount rate and $l_t^* = x_t'\gamma + e_t$ is a *desired* steady-state level of the variable l_t. The x_t series is a $(q \times 1)$ vector of forcing variables while e_t is a white-noise error term known to the firm but not to the econometrician.[2] It is also assumed that the error term is orthogonal to all current information. Since in the empirical section of the paper we will relate the analysis to labour demand, we let l_t be a labour demand variable and x_t be a vector of forcing variables such as real factor prices, output, etc.

As can be seen from equation (1) the individual firms base employment decisions on a discounted sum of future losses in such a way that the actual movements in employment are decomposed into the effects of deviations from the long-run target and the costs associated with

[1] The symmetric quadratic cost function (1) has the advantage of yielding a relatively simple and econometrically tractable labour demand schedule. However, as noted by Nickell (1986), adjustment costs are not necessarily increasing everywhere at the margin, and, despite convexity, hiring and firing costs will typically not be symmetric. Moreover, adjustment costs may contain significant lump-sum cost elements that are abstracted from in our model.

[2] The reason for including the error term e_t, and thus making the desired long-run target of employment stochastic, results from the fact that absence of the e_t term would make the agents' decision rule an entirely nonstochastic function of existing information. The error arising in the resulting estimation equation therefore captures the idea that the econometrician's information set generally will be smaller than that of the individual firm. However, the Campbell and Shiller method (to be discussed below) takes as a starting point the situation where e_t is identically zero. The idea is then to measure how severe the deviations are from the model under this assumption. Several of the contributions mentioned in the introduction take as a benchmark the *exact* model.

changes in employment. The evolution towards the steady-state level will depend upon the magnitude of the relative cost parameter θ, and hence immediate adjustment towards the steady-state level will be sub-optimal unless θ is infinitely large. In the absence of adjustment costs l_t^* may be interpreted as the optimal period by period level of employment, such that the introduction of the second term in equation (1) makes the decision rule dynamic rather than static, as suggested by the variables determining l_t^*.

The solution and stability requirements for this type of model are standard in the literature (see e.g. Sargent, 1979; Nickell, 1985; Gregory *et al.*, 1993). The first-order condition is a second-order difference equation, i.e. an Euler equation of the form

$$\Delta l_t = \beta \mathrm{E}_t \Delta l_{t+1} - \theta(l_t - l_t^*) \tag{2}$$

where E_t is the expectations operator conditional on information at time t. By imposing a transversality condition the equation can be solved using lag-operator techniques to give the following forward-looking labour demand schedule:

$$l_t = \lambda l_{t-1} + (1-\lambda)(1-\beta\lambda)\mathrm{E}_t \sum_{j=0}^{\infty} (\beta\lambda)^j l_{t+j}^* \tag{3}$$

Equation (3) can also be parameterized as

$$\Delta l_t = (\lambda - 1)(l_{t-1} - x'_{t-1}\gamma) + (1-\lambda)\sum_{j=0}^{\infty} (\lambda\beta)^j \mathrm{E}_t \Delta x'_{t+j}\gamma + (1-\lambda)(1-\lambda\beta)e_t \tag{4}$$

where λ is the stable root satisfying the characteristic equation $\beta z^2 - (1+\beta+\theta)z + 1 = 0$ implied by equation (2). The fundamental insight of these formulae is that, due to the costs associated with changing employment, labour demand will adjust gradually towards the optimal level and in part will depend on expected future levels of the forcing (or exogenous) variables. The interpretation of the adjustment parameter $(\lambda - 1)$ in equation (4) is closely linked to the magnitude of the parameter of interest, θ. Note simply that $\theta = \lambda^{-1}(\lambda^2\beta - \lambda(1+\beta) + 1)$ such that values of λ and β close to unity, i.e. adjustment towards the long-run target is slow and losses are highly discounted, are associated with a value of θ close to zero, indicating high costs of adjustment. Of course, the opposite applies when λ is close to zero.

The forward-looking demand schedule in equation (4) may have certain statistical implications under particular conditions. Note that if labour demand and the forcing variables x_t are I(1), then the theoretical equation is essentially an error-correction model written in terms of stationary I(0) variables, where l_t and x_t cointegrate of order CI(1, 1) with cointegrating vector $(1, -\gamma')$. However, an error-correction model derived from an intertemporal optimizing model under rational expectations should not be interpreted as a standard error-correction model where adjustment is entirely the result of discrepancies from equilibrium in the past. To see this, write equation (4) as

$$(l_t - x'_t\gamma) = \lambda(l_{t-1} - x'_{t-1}\gamma) - \lambda\Delta x'_t\gamma + (1-\lambda)\sum_{j=1}^{\infty} (\lambda\beta)^j \mathrm{E}_t \Delta x'_{t+j}\gamma + (1-\lambda)(1-\lambda\beta)e_t \tag{5}$$

Equation (5) states that 'error correction' is both the result of a feedforward mechanism, due to expectations about unknown future variables, *and* a feedback effect due to sluggish adjustment when there are adjustment costs, i.e. through the lagged 'error-correction' term and the observed changes in the forcing variables. Note that if the error term in equation (5) is absent,[3] then the desired employment level l_t^* is simply $x_t'\gamma$ and equation (4) would be what Hansen and Sargent (1981) have termed an *exact linear rational expectations model*.

In the next section we show how the rational expectations hypothesis will impose parameter restrictions on a VAR, and we discuss various ways of how these restrictions and thus the LQAC model, can be tested.

3. TESTING THE RATIONAL EXPECTATIONS RESTRICTIONS

First, we assume that estimates of the cointegration parameters γ and the factor loadings $(1-\lambda)$ have already been obtained. In the empirical section of the paper we will return to this subject. We can thus define the variable[4] $S_t = (1-\hat{\lambda}B)(l_t - x_t'\hat{\gamma}) + \hat{\lambda}\Delta x_t'\gamma$, where B is the lag operator. This variable is economically interesting since, according to equation (5), it is the optimal predictor of the unknown variable $(1-\lambda)\Sigma_{j=1}^{\infty}(\lambda\beta)^j\Delta x_{t+j}'\gamma$, in the special case where e_t is identically zero. Hence S_t is a straightforward analogue of Campbell and Shiller's (1987) 'spread' variable. This implies that S_t should Granger cause Δx_t unless agents only use current and lagged Δx_t to forecast future Δx_t. Next, we define a VAR model for the stationary variables S_t and Δx_t and, based on this model and information available at time t, we can predict the single terms $\Delta x_{t+j}'\gamma$ for the infinite future. The VAR model, assumed to be of order k, reads

$$\begin{pmatrix} \Delta x_t \\ S_t \end{pmatrix} = \sum_{j=j}^{k} C_j \begin{pmatrix} \Delta x_{t-j} \\ S_{t-j} \end{pmatrix} + v_t \tag{6}$$

but for forecasting purposes it is frequently more convenient to write this in first-order companion form as $Z_t = AZ_{t-1} + u_t$, where $Z_t = (\Delta x_t', S_t, \Delta x_{t-1}', S_{t-1}, \dots, \Delta x_{t-k+1}', S_{t-k+1})'$ and A is defined as

$$A = \begin{array}{c} \begin{pmatrix} C_1 & C_2 & \cdots & C_k \\ & \mathrm{I} & & 0 \end{pmatrix} \end{array} \begin{array}{c} q+1 \\ (q+1)\times(k-1) \end{array} \tag{7}$$

where all submatrices C_j are $(q+1)\times(q+1)$ and the remaining zero and identity matrices are of matching dimensions. This way of writing the VAR model is especially attractive since predictions can be easily found from the formula $\mathrm{E}(Z_{t+j} \mid H_t) = A^j Z_t$ with H_t being the information set at time t. It is now possible to define appropriate selection vectors h and g, both of dimension $((q+1)k)\times 1$, such that they pick out $\Delta x_t'\gamma$ and S_t, respectively, from Z_t. That is,

$$\begin{aligned} h'Z_t &= \Delta x_t'\gamma \\ g'Z_t &= S_t \end{aligned} \tag{8}$$

[3] In fact, it is a condition for our analysis that all the forcing I(1) variables included in the firms' information set are also known by the econometrician in the sense that the e_t term is a stationary I(0) term, i.e. the forcing variables cointegrate with l_t. In other words e_t will summarize the influence from variables with a much less dominating trend than the x_t variables.

[4] The cointegration vector can be estimated at the super consistent rate $O_p(T)$ while the remaining terms are $O_p(T^{1/2})$. Hence, in a finite sample, S_t will deviate from the true value of $(1-\lambda)\Sigma_{j=1}^{\infty}(\lambda\beta)^j\mathrm{E}_t\Delta x_{t+j}'\gamma$. However, asymptotically, this discrepancy will be negligible.

These expressions can be used to solve equation (5) for future forcing variables conditional on H_t:

$$S_t = g'Z_t = (1-\lambda)\sum_{j=1}^{\infty}(\lambda\beta)^j h'A^j Z_t + (1-\lambda)(1-\lambda\beta)e_t$$
$$= (1-\lambda)\lambda\beta h'A[\mathrm{I}-\lambda\beta A]^{-1}Z_t + (1-\lambda)(1-\lambda\beta)e_t \tag{9}$$

In the absence of an error term e_t the restrictions read $g' = (1-\lambda)\lambda\beta h'A[\mathrm{I}-(\lambda\beta)A]^{-1}$, or alternatively $g'[\mathrm{I}-\lambda\beta A] = (1-\lambda)\lambda\beta h'A$. If we use the notation

$$C_j = \begin{pmatrix} c_{11}^j & c_{12}^j \\ c_{21}^j & c_{22}^j \end{pmatrix}, \qquad j = 1,2,\ldots,k$$

where the partitioning is made comformably with $(\Delta x_t, S_t)$, then the restrictions on the VAR read

$$\begin{aligned} -c_{21}^j &= (1-\lambda)\gamma' c_{11}^j \qquad \text{for } j = 1,2,\ldots,k \\ -c_{22}^j &= (1-\lambda)\gamma' c_{12}^j \qquad \text{for } j = 2,3,\ldots,k \\ 1-\lambda\beta c_{22}^1 &= (1-\lambda)\lambda\beta\gamma' c_{12}^1 \end{aligned} \tag{10}$$

In the appendix a detailed derivation of these restrictions is given. There will be a total of $k \times (q+1)$ restrictions to be satisfied under the assumption of rational expectations which is exactly one linear restriction on each column of the A matrix. Hence this matrix is singular. If we substitute λ, γ, and β with their estimates we can therefore use, say, a likelihood ratio test to see whether the linear cross-equation restrictions are satisfied by the VAR model (6).

It is important to realize that the restrictions (10) only hold when e_t is identically zero. Allowing e_t to be nonnegligible would imply much more complicated and highly nonlinear cross-equation restrictions, which would make the likelihood ratio test computationally rather burdensome. There is an alternative and much simpler way of testing the restrictions by means of an orthogonality test similar to the market-efficiency tests, well known from the finance literature, where 'excess return' is regressed on information. To construct the orthogonality test for the LQAC model under rational expectations, express equation (5) in terms of S_t and multiply by $(1-(\lambda\beta)^{-1}B)$ in a Koyck transformation. After some manipulations outlined in the appendix, it can be established that

$$\lambda\beta S_t - S_{t-1} + (1-\lambda)\lambda\beta\Delta x_t'\gamma = (1-\lambda)\sum_{j=0}^{\infty}(\lambda\beta)^{j+1}\Delta \mathrm{E}_t \Delta x_{t+j}'\gamma + (1-\lambda)(1-\lambda\beta)(\lambda\beta e_t - e_{t-1}) \tag{11}$$

The first term on the RHS of the expression is a pure innovation under rational expectations, whereas the second term is an MA(1) error. In the case where the firm's decision rule is an entirely deterministic function of existing information, i.e. when the error term e_t is zero, the model is an exact linear rational expectations model as previously discussed. Under this maintained assumption, the model can be tested by regressing the LHS of equation (11) on information variables dated $t-1$ and earlier and testing for their joint significance.[5] If the

[5] In the absence of the error term e_t the unpredictability of the LHS of equation (11), based on information at time $t-1$, can also be shown directly by imposing the restrictions (10) on the VAR model (6) (see the appendix).

desired long-run target of employment is stochastic, and e_t is assumed to be white noise, the model can be tested by regressing the LHS on variables dated $t-2$ and earlier.

A fundamental problem of formal tests of rational expectations models is that frequently they are hard to interpret *economically*. If the test does not reject the model it could be due to low power against important alternatives, and if it does reject, we do not know whether it is caused by fundamental deviations from the model, the information set used in the analysis, or simply by economically unimportant factors (e.g. white-noise measurement errors, etc.). As Campbell and Shiller (1987) put it: '... a statistical rejection of the model [...] may not have much economic significance. It is entirely possible that the model explains most of the variation in [l_t] even if it is rejected at a 5% level' (p. 1063). As an alternative to formal statistical tests of rational expectations models they therefore propose an informal method in order to assess the economic significance of discrepancies from the underlying theoretical model. Their approach is designed to test simple present value models well known from the finance literature,[6] i.e. models where there is no lagged adjustment as in equation (3), but it can be easily generalized to accommodate the LQAC model under rational expectations.

The idea is to focus on the *exact* version of the model, so that e_t measures the deviations from the model. If e_t is identically zero, equation (5) and (9) show that S_t should equal an unrestricted VAR forecast of the present value of future changes in the forcing variables. This VAR forecast is given as

$$S_t^* = \mathrm{E}(S_t \mid H_t) = (1-\lambda)\lambda\beta h' A[\mathrm{I} - \lambda\beta A]^{-1} Z_t \tag{12}$$

Campbell and Shiller argue that if the cross-equation restrictions (corresponding to equation (10)) are statistically rejected, but S_t^*, gerated as in equation (12), moves closely together with S_t, it indicates that the discrepancies from the model through e_t are of minor economic importance, so that there is an important element of truth to the model despite the formal statistical rejection.

4. EMPIRICAL RESULTS FROM DANISH MANUFACTURING

In this section we apply the methods described in the previous section on disaggregated data from Danish manufacturing at a sectoral two-digit level. The data are quarterly seasonally unadjusted time series for the following variables:[7] the number of employed manual workers, l_t, real product wages, w_t, real raw material prices, p_t, and real sales, y_t. The sample covers the period 1974:1 to 1990:4, and all variables are log-transformed. Most of the series exhibit a strong seasonal pattern and to further analyse this we tested for changing seasonality in accordance with the suggestions by Hylleberg *et al.* (1990). No evidence was found in favour of seasonal unit roots though, except for a few of the series across the nine sectors where data are available at a two-digit level. On the other hand, the tests for a unit root at the nonseasonal (zero) frequency were all insignificant.[8] Consequently, we regard all the series as integrated of order one, and to account for the seasonal variation seasonal dummies are included in all subsequent regressions.

In order to implement the VAR method described in Section 3, we need prior estimates of the

[6] Campbell and Shiller (1987) analyse the term structure of interest rates and the efficient stock market model.

[7] The data are collected from various issues of *Statistiske Efterretninger—Industri og Energi* of the Danish Statistical Office. The quarterly series are constructed as quarterly averages from monthly data.

[8] In the auxiliary regressions when testing for unit roots, a time trend and seasonal dummies were included to gain power against the trend stationary and deterministic seasonal alternatives.

cointegration parameters γ and the adjustment cost parameter λ. Cuthbertson and Taylor (1990) propose to use the Johansen (1988, 1991) method to obtain estimates of both γ and λ. However, as we show in Engsted and Haldrup (1993), λ is not uniquely identified from the Johansen VAR estimates in a model of rational expectations. In fact it is only when Δx_t is weakly exogenous w.r.t. the long-run parameters in the equation for Δl_t, *and* Δl_t does not Granger cause the Δx_t variables, that we may use the error-correction coefficient in an error-correction model for Δl_t as an estimate of $(\lambda - 1)$.

This suggests that we start by estimating γ using the Johansen method (or any other cointegration method), and test for long-run weak exogeneity of the forcing variables.[9] We then test for Granger noncausality from Δl_t to Δx_t. In case we do not reject these hypotheses, $(\lambda - 1)$ can be estimated in a single-equation error-correction model for Δl_t, where current and lagged Δx_t are included as regressors.[10] Essentially this corresponds to an unrestricted estimation of equation (4) after solving for future values of Δx_t.

There are nine sectors at a two-digit level in Danish manufacturing and for all nine sectors we carried out Johansen's cointegration analysis. For two of the sectors we found evidence of two significant cointegrating vectors among the four variables. *A priori*, one of the vectors should most naturally be interpreted as a long-run labour demand schedule, whereas the other vector should be interpreted as a long-run real wage equation. We used the switching algorithm described in Johansen (1992) and Johansen and Juselius (1994) to test economically meaningful identifying restrictions on the two vectors, but unfortunately we did not come up with interpretable results.

For the remaining seven sectors we found evidence of one significant cointegration vector, and in three of these (SIC 31, 35, and 39)[11] the hypothesis of long-run weak exogeneity of the forcing variables was either accepted or only marginally rejected at a 5% level. Consequently, we will test the LQAC model under rational expectations for these three sectors. Table I reports the results of the cointegration tests and displays the estimated restricted cointegrating vectors for the three sectors, and the p values for the test of long-run weak exogeneity of the forcing variables.[12] As seen, reasonable and correctly signed estimates of the long-run labour demand elasticities are obtained. Real wage elasticities are found to be negative and smaller than unity, and sales elasticities are found to be positive and also smaller than unity. Real raw material prices have a significant and negative long-run effect on labour demand, except for sector 39. In this sector the estimated raw material price elasticity is $-0{\cdot}007$, and a χ^2 test for a zero coefficient has a p value of 0·90. We have therefore imposed a zero coefficient in estimation as reported in the table. This implies that in the VAR models to be estimated subsequently, Δx_t does not include Δp_t for sector 39.

[9] As noted by Gregory *et al.* (1993) the reduced form equation for Δl_t necessarily implies an MA error term, as opposed to the structural equation for Δl_t. The Johansen VAR is a system of reduced-form equations. We believe, however, that MA errors in this case are only of minor importance for the estimation of γ provided the truncation of the VAR model is of a sufficiently high lag order.

[10] Alternatively, as suggested by Dolado *et al.* (1991), the adjustment cost parameter could be estimated from the Euler equation (2) using instrumental variables, where prior estimates of the long-run parameters γ have been obtained using cointegration methods. We tried this approach on our data set, where we pre-fixed β at 0·99 due to the identification problems inherent in the Euler equation when both β and θ are estimated (see Gregory *et al.*, 1993, pp. 223–7). However, the estimates of θ turned out to be highly insignificant. This was not caused by the use of poor instruments since the correlations between the instruments and the variable being estimated were in all cases quite high. Because of the poor results using the Euler equation approach we did not pursue it any further.

[11] SIC31 is food, beverages and tobacco. SIC35 is chemicals. SIC39 is other industries.

[12] As an alternative to the Johansen method, we also used the non-linear single-equation estimator of Phillips and Loretan (1991). In all three sectors the parameter estimates using the two different methods were very similar.

Table I. Test for cointegration and estimates of the cointegration vectors

		Sector		
		31	35	39
$r \leqslant 3$	L_{max}	34·7[a]	28·1[a]	28·7[a]
	L_{trace}	55·6[a]	53·2[a]	52·6[a]
$r \leqslant 2$	L_{max}	15·0	17·6	15·4
	L_{trace}	20·9	25·1	23·9
$r \leqslant 1$	L_{max}	5·6	5·5	8·2
	L_{trace}	5·9	7·6	8·5
$r \leqslant 0$	L_{max}	0·3	2·1	0·3
	L_{trace}	0·3	2·1	0·3
Cointegration vector	l_t	1·000	1·000	1·000
	w_t	0·732	0·148	0·925
	p_t	0·092	0·459	0
	y_t	−0·746	−0·337	−0·324
χ^2-test for weak exogeneity, p value		0·41	0·09	0·04

Notes:
L_{max} and L_{trace} are the (maximum eigenvalue and trace) likelihood ratio tests for the number of cointegrating vectors (cf. Johansen, 1988, 1991). Critical values for the tests can be found in Johansen and Juselius (1990). [a]Indicates significance at a nominal 5% level. The number of lags in the VAR models are 5, 3, and 4 for sectors 31, 35, and 39, respectively. These lags were chosen to make the residuals serially uncorrelated. In sector 39 an outlier was observed at the first quarter of 1985. This was modelled with a dummy variable. The χ^2-tests for weak exogeneity with respect to long-run parameters are joint tests for weak exogeneity of all the forcing variables.

Table II reports p values for the hypothesis that Δl_t does not Granger cause changes in the forcing variables. In order to check the robustness of the results w.r.t. lag length, the tests were conducted with both two and four lags of the variables. Overall the hypothesis cannot be rejected at a 5% level. The exceptions are sector 31, where Δl_t Granger causes Δw_t at a 2·8% level in the four-lag test, and sector 35 where Δl_t Granger causes Δy_t at a 1·2% level in the two-lag test. Hence, the hypothesis that the forcing variables are generated recursively in relation to labour is roughly supported by the data. This means that we can obtain a consistent estimate of $(\lambda - 1)$ in a single-equation ECM for Δl_t, where, in addition to the error-correction term, current and lagged values of changes in the forcing variables are included as regressors. In the bottom line of Table II we report such estimates for the three sectors. For sectors 31 and 39 the estimates of $(\lambda - 1)$ are around −0·2 irrespective of the number of lags included. In sector 35 the estimate of $(\lambda - 1)$ is somewhat sensitive to the number of lags included. All estimates are correctly signed and significantly different from zero at a 5% level, and they ambiguously indicate that if the underlying LQAC model is true, firms put relatively more weight on costs associated with changing the input of labour than to costs associated with deviating from the long-run target level of employment.

Table III reports summary statistics from the estimation of VAR models for Δx_t and S_t, as described in Section 3, where S_t has been constructed using the estimates of γ and λ from Tables I and II. The first part of the table gives p values for the hypothesis that S_t does not

Table II. Test for Granger non-causality from Δl_t to Δx_t, and single-equation estimates of $(\lambda - 1)$

		Sector					
		31		35		39	
		lag = 2	lag = 4	lag = 2	lag = 4	lag = 2	lag = 4
Causality-test							
p values	Δw_t	0·799	0·078	0·996	0·431	0·149	0·311
	Δy_t	0·356	0·070	0·012	0·162	0·803	0·939
	Δp_t	0·995	0·551	0·505	0·435	—	—
Estimate of $(\lambda - 1)$		−0·166	−0·197	−0·355	−0·208	−0·225	−0·188
		(0·055)	(0·057)	(0·068)	(0·093)	(0·065)	(0·070)

Notes:
The causality tests give the p value for the hypothesis that Δl_t does not Granger cause Δw_t, Δy_t, and Δp_t, respectively. The estimates of $(\lambda - 1)$ gives the estimates of the error correction coefficient in a single-equation error correction model for Δl_t with two and four lags of Δw_t, Δy_t and Δp_t. The numbers in parentheses are standard errors.

Granger cause Δw_t, Δy_t, and Δp_t, respectively. This hypothesis cannot be rejected, except in one case. This implies either that the LQAC model under rational expectations is wrong or that firms do not use information besides current and lagged forcing variables to forecast future forcing variables. In the middle part of the table we report p values for the tests of the LQAC model under rational expectations. We preset the value of the discount factor β at 0·99.[13] The results are not in any way sensitive to the precise value of β. In both the case of a deterministic decision rule ($e_t = 0\ \forall t$) and a stochastic long-run target (e_t white noise), we strongly reject the rational expectations restrictions.[14] To see whether this rejection is caused by the model being fundamentally wrong, or by transitory and economically unimportant factors,[15] we finally calculate the unrestricted VAR forecast of the present value of future changes in the forcing variables, S_t^*, and compare its movement with the movement in S_t. The lower part of Table III gives the correlation coefficients between the two S_t variables, and the ratio of their standard deviations. Both of these should be close to unity if the LQAC model under rational expectations has any empirical content. As seen, the correlations are below 0·5 in all three sectors, and S_t varies much more than S_t^*. See also Figures 1–3, where S_t and S_t^* are generated from the two-lag VAR.

These results indicate that there is not much empirical content to the LQAC model under rational expectations in explaining labour demand in Danish manufacturing. The apparent failure of the LQAC model under rational expectations might be due to the use of wrong values of the adjustment cost parameter λ in the construction of S_t^*. In estimating these values we have assumed that the forcing variables are generated recursively in relation to labour demand. The

[13] Presetting of β follows a long tradition in this literature since the discount rate cannot be identified in general (see e.g. Gregory *et al.*, 1993). The choice of $\beta = 0·99$ in our case seems natural for quarterly data.

[14] It is not possible to conduct the likelihood ratio test of the restrictions in the VAR models with four lags in sectors 31 and 35 because the unrestricted model contains more parameters than observations.

[15] An obvious reason for such deviations in our context is that we use sales instead of output, because it is not possible to obtain quarterly data for output at a sectoral level in Denmark. That is, y_t is definitely measured with error which could be the cause of the statistical rejection.

Table III. Summary statistics from VAR models for Δx_t and S_t

		Sector					
		31		35		39	
		lag = 2	lag = 4	lag = 2	lag = 4	lag = 2	lag = 4
Causality test							
p values	Δw_t	0·759	0·104	0·802	0·815	0·394	0·293
	Δy_t	0·263	0·298	0·024	0·126	0·935	0·932
	Δp_t	0·675	0·397	0·216	0·247	—	—
Tests of RE restrictions							
	χ_1^2	57·89	—	67·79	—	68·96	77·08
		(0·000)		(0·000)		(0·000)	(0·000)
	χ_2^2	129·04	328·8	148·49	256·38	211·25	276·66
		(0·000)	(0·000)	(0·000)	(0·000)	(0·000)	(0·000)
	χ_3^2	45·64	180·74	113·86	145·13	17·59	52·58
		(0·000)	(0·000)	(0·000)	(0·000)	(0·007)	(0·000)
Correlation(S, S^*)		0·089	−0·079	0·454	0·194	0·327	0·122
$\sigma(S^*)/\sigma(S)$		0·119	0·299	0·148	0·140	0·106	0·177

Notes:
The causality tests give the p value for the hypothesis that S_t does not Granger cause Δw_t, Δy_t, and Δp_t, respectively. χ_1^2 gives the likelihood ratio test statistic for the RE restrictions under the assumption that $e_t = 0$. χ_2^2 gives the orthogonality test of the restrictions under the assumption that $e_t = 0$, and finally χ_3^2 gives the orthogonality test for the restrictions under the assumption that e_t is a white-noise process. In the orthogonality tests, allowing e_t to be white noise, it was in some cases necessary to invoke the Newey and West (1987) correction to obtain a positive definite covariance matrix. The numbers in parentheses are p values. All variables in the VAR are in deviations from a constant and three seasonal dummies.

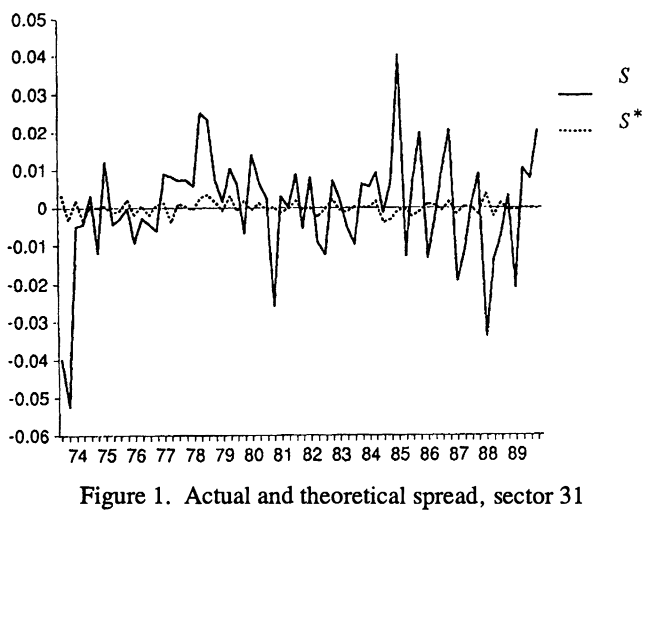

Figure 1. Actual and theoretical spread, sector 31

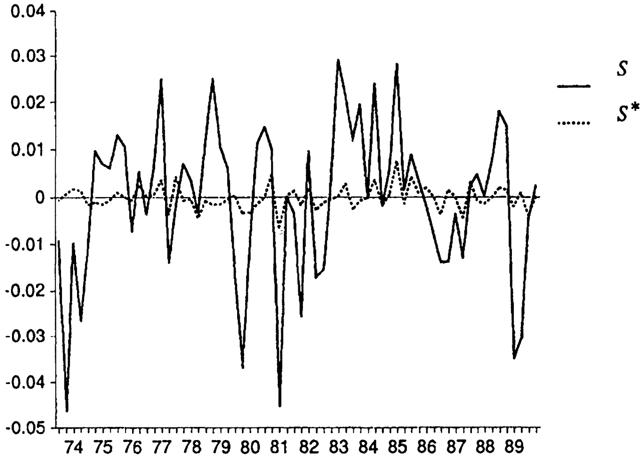

Figure 2. Actual and theoretical spread, sector 35

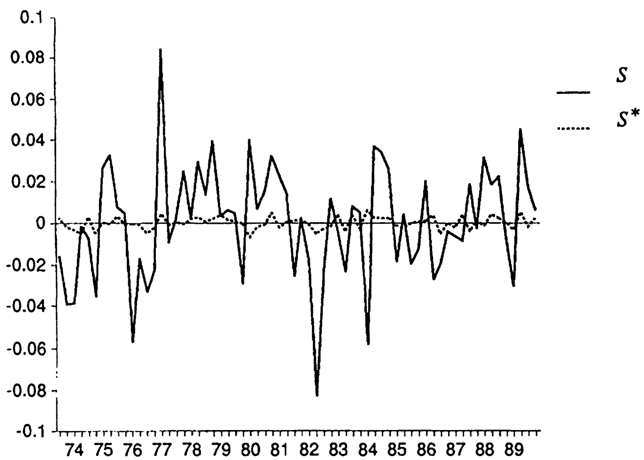

Figure 3. Actual and theoretical spread, sector 39

tests tend to support this assumption, though not unambiguously. We therefore constructed estimates of S_t^* using different values of λ in the range of 0·1 to 0·9, to see whether there exists values of λ that produce a high degree of comovement of S_t and S_t^*. However, the low degree of comovement was apparent for all values of λ in all three sectors.

5. CONCLUSION

In this paper we have analysed the LQAC model under rational expectations by allowing conditioning and forcing variables to exhibit stochastic nonstationarity. In particular, we have presented a generalization of the Campbell and Shiller method to test present value models under rational expectations to the case of noninstantaneous adjustment as a result of adjustment costs. The theoretical model implies linear restrictions across equations in a particular VAR model; restrictions that are easily testable by, say, a LR test. The restrictions can also be formulated as a single-equation orthogonality condition which is similar in nature to the orthogonality market-efficiency tests widely used in the empirical finance literature. If a particular present value model is statistically rejected by the data this can be due to several reasons, some of which are not entirely the result of fundamental *economic* deviations from the model (for instance, measurement errors). It is therefore interesting to get an empirical fit of the model in order to obtain a measure of the discrepancies. The Campbell and Shiller method was extended in this respect, and we showed how an *exact* rational expectations version of the model could be used as a benchmark for a comparison of the predictions of the model and the actual observations. Finally, we used the derived techniques to analyse labour demand in Denmark at a sectoral level, but we did not find any convincing evidence that the LQAC model in this case could provide a good description of the data.

APPENDIX

This appendix serves to clarify some of the derivations in the main test.

Derivation of the Cross-equation Restrictions (10)

Note that in accordance with equation (8) the selection vectors g and h are defined as $g' = (0, 1, 0, \ldots, 0)$ and $h' = (\gamma', 0, \ldots, 0)$, respectively. Observe that equation (5) can be expressed as

$$S_t = g'Z_t = (1-\lambda)\sum_{j=1}^{\infty} (\lambda\beta)^j h'A^j Z_t + (1-\lambda)(1-\lambda\beta)e_t \tag{A1}$$

but since $E_t(Z_{t+j}) = A^j Z_t$ this implies that the expectation of the sum in this expression can be written as

$$\begin{aligned}
&(1-\lambda)[\lambda\beta h'AZ_t + (\lambda\beta)^2 h'A^2 Z_t + (\lambda\beta)^3 h'A^3 Z_t + \ldots] \\
&= (1-\lambda)\lambda\beta h'A[I + \lambda\beta A + (\lambda\beta)^2 A^2 + (\lambda\beta)^3 A^3 + \ldots]Z_t \\
&= (1-\lambda)\lambda\beta h'A[I - \lambda\beta A]^{-1} Z_t
\end{aligned}$$

This proves equation (9). It can now be easily seen that provided the e_t term is absent, the cross-equation restrictions should satisfy

$$g'[I - \lambda\beta A] = (1-\lambda)\lambda\beta h'A \tag{A2}$$

The elements of the C_j matrices for $j = 1, 2, \ldots, k$ refer to the VAR parameters associated with the jth lag where the partitioning into c_{11}^j, c_{12}^j, c_{21}^j, and c_{22}^j is made comformably with $(\Delta x_t', S_t)'$. Hence, for each j defined in equation (6) we have

$$C_j = \begin{array}{c} \begin{pmatrix} c_{11}^j & c_{12}^j \\ c_{21}^j & c_{22}^j \end{pmatrix} \begin{array}{c} q \\ 1 \end{array} \\ \begin{array}{cc} q & 1 \end{array} \end{array}$$

By using this definition and the expression for A in equation (7) it is possible to write the parametric restrictions (A2) in the following way:

$$(0,1,0,,...,0)\left[\begin{pmatrix} I & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & I & 0 \\ 0 & 0 & 0 & I \end{pmatrix} - \lambda\beta \begin{pmatrix} c_{11}^1 & c_{12}^1 & c_{11}^2 & c_{12}^2 & \dots & c_{11}^k & c_{12}^k \\ c_{21}^1 & c_{22}^1 & c_{21}^2 & c_{22}^2 & \dots & c_{21}^k & c_{22}^k \\ & & I & & & 0 & \end{pmatrix}\right]$$

$$= (1-\lambda)\lambda\beta(\gamma',0,...,0)\begin{pmatrix} c_{11}^1 & c_{12}^1 & c_{11}^2 & c_{12}^2 & \dots & c_{11}^k & c_{12}^k \\ c_{21}^1 & c_{22}^1 & c_{21}^2 & c_{22}^2 & \dots & c_{21}^k & c_{22}^k \\ & & I & & & 0 & \end{pmatrix}$$

and by writing out these expressions:

$$(-\lambda\beta c_{21}^1, 1-\lambda\beta c_{22}^1, -\lambda\beta c_{21}^2, -\lambda\beta c_{22}^2, \dots, -\lambda\beta c_{21}^k, -\lambda\beta c_{22}^k)$$
$$= (1-\lambda)\lambda\beta(\gamma' c_{11}^1, \gamma' c_{12}^1, \gamma' c_{11}^2, \gamma' c_{12}^2, \dots, \gamma' c_{11}^k, \gamma' c_{12}^k)$$

Hence the restriction associated with the first element reads

$$-c_{21}^1 = (1-\lambda)\gamma' c_{11}^1$$

while the second restriction is

$$1-\lambda\beta c_{22}^1 = (1-\lambda)\lambda\beta\gamma' c_{12}^1$$

The remaining restrictions can be established accordingly and equation (10) summarizes all these in a compact form.

Derivation of the Orthogonality Condition (11)

Consider a Koyck transformation of equation (A1) using the polynomial $(1-(\lambda\beta)^{-1}B)$:

$$S_t - (\lambda\beta)^{-1} s_{t-1} = (1-\lambda)\sum_{j=1}^{\infty}(\lambda\beta)^j \mathrm{E}_t \Delta x'_{t+j}\gamma - (1-\lambda)\sum_{j=1}^{\infty}(\lambda\beta)^{j-1}\mathrm{E}_{t-1}\Delta x'_{t+j-1}\gamma$$
$$+ (1-\lambda)(1-\lambda\beta)(1-(\lambda\beta)^{-1}B)e_t$$

By collecting terms, multiplying by $\lambda\beta$, and abstracting from the error term, which is obviously given, we obtain

$$\lambda\beta S_t - S_{t-1} = (1-\lambda)\lambda\beta[\lambda\beta \mathrm{E}_t\Delta x'_{t+1}\gamma + (\lambda\beta)^2\mathrm{E}_t\Delta x'_{t+2}\gamma + \dots]$$
$$-(1-\lambda)\lambda\beta[\mathrm{E}_{t-1}\Delta x'_t\gamma + \lambda\beta\mathrm{E}_{t-1}\Delta x'_{t+1}\gamma + (\lambda\beta)^2\mathrm{E}_{t-1}\Delta x'_{t+2}\gamma + \dots] + error$$

But since Δx_t is already in the information set this reads

$$\lambda\beta S_t - S_{t-1} + (1-\lambda)\lambda\beta\Delta x'_t\gamma = (1-\lambda)\lambda\beta[(E_t\Delta x'_t\gamma - E_{t-1}\Delta x'_t\gamma)$$
$$\lambda\beta(\mathrm{E}_t\Delta x'_{t+1}\gamma - \mathrm{E}_{t-1}\Delta x'_{t+1}\gamma) + (\lambda\beta)^2(\mathrm{E}_t\Delta x'_{t+2}\gamma - \mathrm{E}_{t-1}\Delta x'_{t+2}\gamma) + \dots] + error$$

Equation (11) is a more compact way of writing this.

In footnote 5 we conjecture that the orthogonality condition (11) can be derived by imposing the restrictions (10) on the VAR. To simplify the notation, assume that the VAR model for

$(\Delta x_t, S_t)$ is of first order, $k = 1$. Therefore

$$\begin{pmatrix} \Delta x_t \\ S_t \end{pmatrix} = \begin{pmatrix} c_{11}^1 & c_{12}^1 \\ c_{21}^1 & c_{22}^1 \end{pmatrix} \begin{pmatrix} \Delta x_{t-1} \\ S_{t-1} \end{pmatrix} + error \tag{A3}$$

The restrictions following equation (10) read

$$c_{21}^1 + (1-\lambda)\gamma' c_{11}^1 = 0$$

$$c_{22}^1 + (1-\lambda)\gamma' c_{12}^1 = (\lambda\beta)^{-1}$$

Now, multiply the Δx_t equation by $(1-\lambda)\gamma'$ and add the S_t equation in equation (A3). Hence it can be established that

$$S_t + (1-\lambda)\gamma'\Delta x_t = (c_{21}^1 + (1-\lambda)\gamma' c_{11}^1)\Delta x_{t-1} + (c_{22}^1 + (1-\lambda)\gamma' c_{12}^1)S_{t-1} + error = (\lambda\beta)^{-1}S_{t-1} + error$$

It is now easy to see that

$$\lambda\beta S_t + \lambda\beta(1-\lambda)\gamma'\Delta x_t - S_{t-1} = error$$

which is exactly the left-hand side of equation (11). A higher-order VAR model would have further zero restrictions on the higher-order terms but would lead to the same algebraic expression.

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