10. Modelling stochastic technological change in economy and environment using the Kalman filter

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This chapter reports on empirical work (Perrings and Stern 2000; Stern 1994) that uses the Kalman filter to estimate stochastic trends in the context of resource use models. This modelling approach treats changes in the environment and changes in the production possibilities of the economy as similar processes, which in both cases can be seen as changes in either capital stocks or changes in technology. The two case studies are a model of production and technological change in the US macroeconomy in the post-war period, and a model of rangeland utilization and degradation in Botswana in the 30 years to the mid-1990s.

Perrings (1987) presents a vision of a dynamic, evolving economy that receives inputs from its environment and returns surplus outputs to its environment. These surplus outputs substantively change the nature of the resource base on which the economy depends and the changing nature of the resource structure precipitates technological change within the controlled economy itself. Technological change and controlled capital accumulation within the economy forces uncontrolled capital accumulation and technological change in the environment (O'Connor 1993). Perrings modelled this system using a von Neumann-type technology and the mass balance principle as key features. This vision was extended and refined by O'Connor (1991) to include energy flows and thermodynamic considerations regarding energy.

The framework presented in this chapter is nowhere near as complete or encompassing. However, it does incorporate some aspects of such a system. Its primary advantage is that it is an empirical approach utilizing advanced econometric techniques to describe the state and evolution of technology. Unlike the Perrings and O'Connor models, the models in this chapter utilize neoclassical principles of optimization. Additionally, the US model embodies a neoclassical production function that allows continuous substitution of factor inputs within a given state of technology. The technology in the rangeland model consists of a group of logistic growth functions.

Conventional econometric modelling of agricultural and industrial production technologies (for example Capalbo 1988; Berndt and Khaled 1979) has assumed that such systems can be approximated by deterministic production technologies that are inherently linear in the parameters. The stochastic components of these models are stationary random variables due to optimization errors by producers. There are two reasons why this approach is inappropriate as a model of joint economy-environment systems. The first is that they are probably inappropriate as a model of industrial systems. Technological change is now widely seen as a non-stationary stochastic process (Slade 1989; Solow 1994). Second, the natural environment is an additional source of stochastic variation, uncertainty, unpredictability, and evolutionary and sometimes 'surprising' behaviour (O'Connor 1993; Perrings 1987).

Cointegration modelling and Kalman filtering are two approaches to the econometric modelling of non-stationary systems that have been rapidly introduced to all areas of applied econometrics (Cuthbertson et al. 1992). Cointegration modelling (Engle and Granger 1987) assumes that a linear combination of random variables is stationary.[1] Kalman filtering (Kalman 1960; Kalman and Bucy 1961) can be used to model explicitly non-stationary random variables. It has been used in this context to model technological change as a stochastic trend (Harvey and Marshall 1991; Slade 1989; Stern 1994). Extremely complex and non-linear models may be amenable to econometric estimation using the Kalman filter. Both studies in this chapter use Kalman filter techniques. Cointegration modelling only enters explicitly to the extent that the equations in the Botswana model incorporate a form of error correction mechanism. Implicitly, we test all equations for stationary residuals and hence for the presence of cointegration.[2]

Changes in the quality of environmental resources such as rangelands in sub-Saharan Africa can be visualized as a process of uncontrolled technological change in the environment. As such they can be modelled in a similar way to technological change in controlled economic systems. In this chapter, we use the Kalman filter to model factor-augmenting technological change trends in the US macroeconomy in the post-war period. Standard linear regression techniques are of no use in estimating this type of model where the trend variables are stochastic rather then simple deterministic trends. This model is a fairly standard econometric model of technological change in the economy though we know of no other study that actually estimates multiple stochastic technical change trends. The main substantive point of interest for ecological economists and environmental management scholars is the estimated trend in autonomous energy efficiency.[3]

We also use the Kalman filter to model the current and climax state of rangeland in Botswana in a 30-year period up to the mid-1990s within an optimal control model of pastoralists' behaviour. Both state variables are unobserved by

the econometrician and represent the state of natural technology in livestock production or dually the level of natural capital present. Of particular interest is the distinction between short-run, reversible rangeland degradation, represented by declines in the current state of the rangeland, and long-run and irreversible rangeland degradation, represented by declines in the climax state of the rangeland. We interpret the latter to be the result of the loss of resilience in the agro-ecosystem.

The advantage of this modelling approach is that we do not need to be able to directly measure the availability of natural capital stocks in order to integrate a simple model of the ecology of the system into a behavioural model of the economic system. This generalized technological change approach may have many other integrative applications in ecological economics.

The remainder of the chapter is divided into three main parts. The next part covers the theory of generalized technological change and state space models and the Kalman filter. The third part presents the empirical examples and the fourth provides some conclusions.

THEORY

Generalized Technological Change

Let us examine in more detail the relationship between the conventional definition of technology and the broader definition proposed here. In a general production system any aggregate indicator of the state of technology is a composite of the state of the natural resource base and the state of technology in the usual sense (Cleveland and Stern 1993; Stern 1999a). More specifically, assume that technology is given by the following transformation frontier:

$$Q = f(A_1 X_1, \ldots, A_n X_n, B_1 R_1, \ldots, B_m R_m, N) \tag{10.1}$$

R is a vector of resource inputs (for example the area of agricultural land, stock of petroleum in a reservoir) and N is a vector of additional environmental variables such as rainfall and temperature. The X_i are other factors of production controlled by the extractor (such as capital, labour, energy and materials), and the A_i and B_i are augmentation factors associated with the respective factors of production. Factor augmentation is a (fairly weak) restriction on the possible nature of technological change. It specifies that technical change increases or decreases the effective quantity of each factor of production available per crude unit of the input used.[4] Taking the derivative of lnQ with respect to time yields:

$$\dot{Q} = \sum_i \sigma_i \dot{A}_i + \sum_j \rho_j \dot{B}_j + \sum_i \sigma_i \dot{X}_i + \sum_j \rho_j \dot{R}_j + v\dot{N} \tag{10.2}$$

where the σ_i, ρ_i, and v are the output elasticities of the various inputs. A dot on a variable indicates the derivative of the logarithm with respect to time. Four measures of resource productivity or resource scarcity in a cost of production sense (Cleveland and Stern, 1993; Stern, 1999a) can be derived from (10.2). The crudest indicator is resource productivity (Q/R):

$$\dot{Q} - \dot{R} = \sum_i \sigma_i \dot{A}_i + \sum_j \rho_j \dot{B}_j + \sum_i \sigma_i \dot{X}_i + v\dot{N} \qquad (10.3)$$

where R is an aggregate of the resource inputs. Examples of this indicator are energy-intensity (E/GDP) and crop yields. This indicator is not very informative about likely long-run developments in resource availability because it is likely to be dominated in the short run at least by changes in the quantities of other inputs X.

Multifactor productivity (*MFP*) is a measure of the quantity of produced inputs required to extract a unit of resource commodity and is thus an indirect measure of the combined state of technology and state of nature and the availability of resources (see Stern, 1999a). This measure is a generalization of the unit cost indicator of resource scarcity introduced by Barnett and Morse (1963). An advantage of this indicator is that we do not need any data about the state of the resource stock, R. The change in *lnMFP* is given by:

$$\dot{MFP} = \dot{Q} - \sum_i \sigma_i \dot{X}_i = \sum_i \sigma_i \dot{A}_i + \sum_j \rho_j \dot{B}_j + \sum_j \rho_j R_j + vN \qquad (10.4)$$

Thus moves in this indicator are the sum of the four terms on the *RHS* of (10.4), respectively:

1. Technical change
2. Resource depletion or augmentation
3. Change in the dimension of the resource stock, for example area farmed
4. Change in environmental variables such as rainfall and temperature in agriculture

The sum of terms 1, 2, and 4 are what energy analysts call resource quality (Gever et al. 1986). This definition of resource quality allows changes in the state of technology to compensate for a decline in the physical quality of the resource. MFP is not affected by the prices and availability of those other inputs that can obscure the long-term trends in resource quality and availability.[5]

When we have data available on the extent of the resource base, we can compute total factor productivity (*TFP*), which expresses the productivity of the joint system:

$$\dot{TFP} = \dot{Q} - \sum_i \sigma_i \dot{X}_i - \sum_j \rho_j R_j = \sum_i \sigma_i \dot{A}_i + \sum_j \rho_j \dot{B}_j + vN \qquad (10.5)$$

This indicator is identical with the resource quality concept mentioned above. We can obtain even more information by breaking the right-hand side of (10.5) into its components – the factor augmentation trends. The augmentation trends tell us about the contribution of the relevant inputs to productivity holding the quantities and effectivities of all the other inputs constant. In the US growth model example, one of the augmentation trends estimated is the autonomous energy efficiency. In the Botswana case study, the main indicator is the carrying capacity of the rangeland or the 'state of the rangeland'. The former trend is mainly due to changes in technology that allow consumers to use energy more or less effectively. The latter trend is more in the nature of a change in the natural capital stock, but it can be treated as if it was a change in technology.

Recent research on technological change has emphasized that to a large extent technological change is endogenous – rather than changes arriving as exogenous 'manna from heaven' they may occur as a result of the economic process and agents may invest in research and development. In the US example we assume that technological change is exogenous. This does not mean that technological change occurs at a constant rate or that it is unaffected by economic factors. Quite to the contrary, we assume that the rate of technological change varies over time as it follows a stochastic time path. Economic events and variables may indeed affect the course of this path; however, the econometric model does not specify the ways in which this happens. Technology is exogenous in the sense that economic agents are not free to choose the technology with which they produce. However, following standard neoclassical assumptions they are free to choose the technique that they use from among those afforded by the technology. Therefore, optimization processes are constructed for the purposes of econometric estimation assuming that [at least some] prices, technology and uncontrolled inputs are given, but agents are free to choose quantities of controlled inputs.

On the other hand, in the Botswana case study changes in the state of the rangeland are partly endogenous – grazing by cattle affects the state of the rangeland – and partly exogenous – the effects of rainfall and random shocks. However, we assume that pastoralists do not take the state of the rangeland into account in their decision-making. Their impact on the rangeland is treated as an external cost.

State Space Models and Kalman Filter

The Kalman filter is an algorithm for estimating unobserved time-varying variables and has numerous applications in modern time series econometrics. In our application we use the filter to estimate unobserved stochastic trends.[6] The first step in applying the Kalman filter to an estimation problem is to

reformulate the model in question in terms of a state space model. A non-linear generalization of the linear state space model is given by (De Jong, 1991a, 1991b; Harvey, 1989):

$$y_t = z(a_t) + E(a_t)\, u_t \qquad t = 1, \ldots, T \qquad (10.6)$$

$$a_{t+1} = r(a_t) + H(a_t)\, u_t \qquad t = 1, \ldots, T \qquad (10.7)$$

where equations (10.6) are the measurement equations and equations (10.7) are the transition equations; y_t is the vector of 'dependent' variables, the observations; a_t is a vector of unobserved stochastic state variables; u_t is a vector of normally distributed disturbances with zero mean and covariance $\sigma_u^2 I$ (and is assumed to be serially uncorrelated and uncorrelated with $a()$; $z()$, $r()$, $E()$, and $H()$ are possibly non-linear functions of the state vector. In the Botswana case study, $E()$ and $H()$ are constant matrices. Additionally in the US study, $r()$ is a linear function.

As the state variables are unobserved and the current state depends on previous unobserved states, the Kalman filter must be used to estimate the current state vector. The filter is also used to compute the prediction error decomposition of the likelihood function. We use the Davidon–Fletcher–Powell quasi-Newton algorithm (Greene 1990) to maximize this likelihood function with respect to the fixed hyperparameters that define the functions in (10.6) and (10.7). The derivatives are calculated by the finite difference method. Given maximum likelihood estimates of the hyperparameters, the Kalman filter produces maximum likelihood estimates of the state variables using only data for previous periods. Given these estimates, a smoother algorithm (De Jong 1991a, 1991b) is used to calculate values for the unobserved state variables utilizing the entire data set. We use the extended Kalman filter suitable for such non-linear state space models. Details of the use of the Kalman filter in this context are given by De Jong (1991a, 1991b), Harvey (1989), Harvey and Marshall (1991), Slade (1989), and Stern (1994).

APPLICATIONS

Energy and Growth

There has been extensive debate concerning the trend in energy efficiency in the developed economies, especially since the two oil price shocks of the 1970s. Taking the example of the US economy, energy consumption hardly changed in the period 1973 to 1990 (Figure 10.1). This was despite a significant increase in GDP. These facts are indisputable. What has been the subject
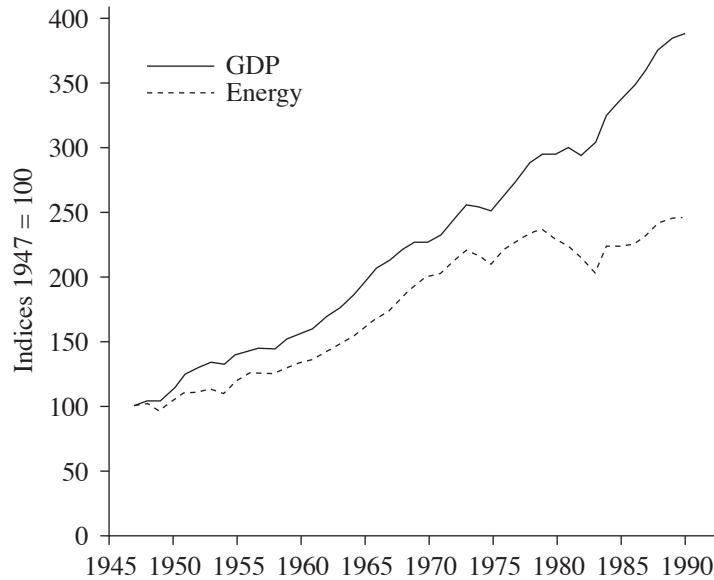
Figure 10.1   US gross energy use and GDP

of argument is what were the reasons for the break in the trend. It is commonly asserted that there has been a decoupling of economic output and resources, which implies that the limits to growth are no longer as restricting as in the past (for example Bohi 1989; IBRD 1992). There are four main explanations of decoupling:

1. Decoupling may be due to shifts from lower-quality fuels such as coal to higher quality fuels such as electricity, which are more productive (Kaufmann 1992; US Congress 1990). Figure 10.2 shows that when we adjust energy use for shifts in energy quality, much less decoupling is evident.
2. Decoupling could be due to substitution of other inputs for energy.
3. Shifts in the output mix might result in decoupling if economies dematerialize as the share of the service sector in economic activity grows over the course of economic development.
4. Finally, a fourth possible cause of decoupling is growing autonomous energy efficiency.

Jorgensen and Wilcoxen (1993) estimated that autonomous energy efficiency is declining. Berndt et al. (1993) use a model in which this index is
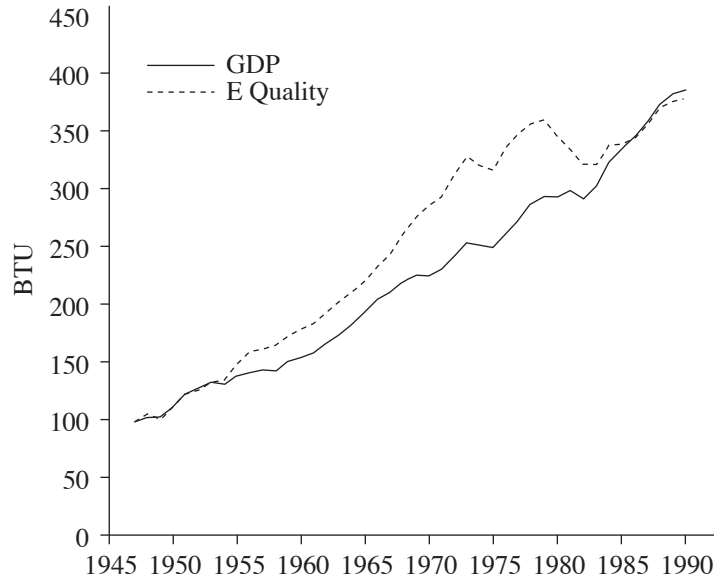
Figure 10.2   USA: quality-weighted final energy use and GDP

assumed to change at a constant rate. They estimate that in the US manufacturing industry between 1965 and 1987, the energy augmentation index was increasing at between 1.75 per cent and 13.09 per cent per annum depending on the assumptions made.

Perhaps these rather inconsistent and wide-ranging estimates are due to the inappropriate assumption that the trend is deterministic. We can use the Kalman filter to estimate an autonomous energy efficiency trend that is stochastic rather than deterministic. The trend is estimated as a factor-augmenting technical change trend alongside those for capital and labour by using a group of equations derived from a macroeconomic production function.

We use a similar method to Harvey and Marshall (1991) with the following modifications. Like Slade (1989) and Darby and Wren-Lewis (1992), we assume that the trends follow a local linear trend (Harvey 1989), rather than a random walk with drift. We do not assume constant returns to scale (but do assume homotheticity) and use a production function rather than a cost function.[7] Also, we estimate the model in the time domain rather than the frequency domain and do not make the assumption of statistical homogeneity.

Similarly to Harvey and Marshall (1991), we assume that factor markets are competitive. It is not assumed that output markets are competitive. We also

assume that a translog function can provide a reasonable approximation to the underlying production technology. We assume that there is weak separability between the two groups capital–labour–energy (KLE), and materials, which allows us to omit materials from models of the marginal product of the other factors (Lakshmanan et al. 1984). This is the only assumption required to estimate the factor share equations (see below) with the omission of materials. However, in order to estimate an output equation excluding a materials variable, we have to assume also that non-energy materials are strictly complementary to aggregate KLE input and therefore have a zero marginal product. Any increase in output due to an increase in materials use with constant KLE input is credited to technical change. This is a strong assumption. While it could be argued that these are reasonable approximations in a manufacturing industry, they are clearly unreasonable approximations in an industry such as agriculture where fertilizers, pesticides, water and so on can be used in varying proportions and clearly do have a marginal product.

In accordance with Harvey and Marshall (1991), it is assumed that technical change is both of the factor-augmenting type represented by three stochastic trend variables, A_K, A_L, and A_E, and also of a factor neutral type represented by a stochastic trend A_0. However, such a trend is unidentifiable in the model developed here and therefore it was dropped.[8] The translog production function for period t, imposing symmetry restrictions (see Berndt and Christensen 1973) on the cross-product coefficients π_{ij}, is:

$$\ln Q_t = \pi_0 + \sum_i \pi_i \ln(X_{it} A_{it}) + \tfrac{1}{2} \sum_i \sum_j \pi_{ij} \ln(X_{it} A_{it}) \ln(X_{jt} A_{jt}) \qquad (10.8)$$

where Q is output and the X are the various factor inputs. Following Kim (1992), and given the above assumptions, we derive inverse factor demand functions from the production function that determine the price of each of the three factors of production. These demand functions yield after various manipulations, the cost share equations:

$$S_{it} = (\partial C_t / \partial Q_t) \, [\pi_i + \sum_j \pi_{ij} \ln A_{jt} + \sum_j \pi_{ij} \ln X_{jt} + \varepsilon_{it}] \qquad (10.9)$$

where C is total cost and the S_i the shares of each factor in costs. We assume that the production function is homogeneous, but do not impose constant returns to scale. As the cost shares sum to a constant in every period, the covariance matrix of their disturbances is singular, that is $\sum_i \varepsilon_i = 0$ and it is not possible to obtain a maximum likelihood estimate of all three equations jointly (Barten 1969). We chose to drop the energy share equation.

In order to estimate all three augmentation trends, at least three equations are required. The obvious third equation is the production function. However, the production function itself involves multiples of the unobserved augmentation

variables, which cannot then be estimated using the diffuse Kalman filter.[9] For this reason the output equation is not the production function (10.8) but is instead based on integrating (10.2) under the assumption of factor market equilibrium and substituting into (10.8):

$$\ln Q_t = \pi_0 + (\partial C_t / \partial Q_t)^{-1} [\sum_j S_{it} \ln A_{jt} + \sum_j S_{it} \ln X_{jt} + \varepsilon_{Qt}] \qquad (10.10)$$

The local linear trend model follows a random walk with a time-varying drift that itself follows a random walk:

$$\ln A_{it} = \ln A_{it-1} + \gamma_{it-1} + \eta_{Ait} \qquad (10.11)$$

$$\gamma_{it} = \gamma_{it-1} + \eta_{\gamma it} \qquad (10.12)$$

All the error terms η are assumed to be uncorrelated. The elements of a_t in (10.7) are therefore:

$$a_t = [\ \ln A_{Kt},\ \ln A_{Lt},\ \ln A_{Et}, \gamma_{Kt},\ \gamma_{Lt},\ \gamma_{Et}]' \qquad (10.13)$$

where γ_{Kt}, γ_{Lt}, and γ_{Et} are the stochastic trend terms and the transition matrix in (10.7) is:

$$R = \begin{bmatrix} I_3 & I_3 \\ 0_3 & I_3 \end{bmatrix} \qquad (10.14)$$

The initial state of A is set to zero with zero variance, while γ has a diffuse prior distribution. This indexes the augmentation trends to one in the first year. The observed variables are also indexed to one.

To summarize – two of equations (10.9) are estimated for labour and capital together with (10.10). We use De Jong's (1991a, 1991b) diffuse Kalman filter algorithm. In total there are six parameters of the production function that must be estimated by maximum likelihood: π_0, π_K, π_L, π_E, π_{KK}, π_{KL}, and π_{LL}, which form the parameters of $z()$ in (10.6) as well as five in the constant covariance matrix E and six in H. An estimate of the error variance of the first equation σ^2_u that is concentrated out of the likelihood function is also produced. Maximum likelihood is performed iteratively using the Broyden, Fletcher, Goldfarb and Shanno approximation of the Hessian matrix and finite difference derivatives.

Full details of the data employed are provided in Stern (2000). Labour is measured in hours worked by full- and part-time employees in domestic industries. Capital is measured by a Divisia index aggregating producer's private

capital. Energy is measured by a Divisia index aggregating a variety of fuel types (shown in Figure 10.2). Output is gross output calculated using a Divisia index as the real value of GDP and energy.[10] Due to this high level of aggregation, it is possible that the estimate of autonomous energy efficiency will incorporate the effects of some aspects of structural change on the output side of the economy (Solow 1987). The time period employed is 1948–1990.

The estimates of the hyperparameters, their standard errors and the estimate of σ^2_u are presented in Table 10.1. Most of the parameters are highly significant. Some of the error variances are insignificant as is π_{LL}. The main features of the results concern the estimated production function parameters and the stochastic properties of the technical change trends. The production technology is characterized by increasing returns to scale. The degree of returns to scale is 1.146. This compares to Kim's (1992) estimate for US

Table 10.1   Maximum likelihood estimates of hyperparameters in the US macro model

Parameter	Estimate (standard error in parentheses)	Parameter	Estimate (standard error in parentheses)
π_K	0.4819 (0.0312)	$E_{3,2}$	–0.3787 (0.1323)
π_L	0.5739 (0.0388)	$E_{3,3}$	5.4255e–04 (0.5884)
π_E	0.0902 (7.4482E–03)	$H_{1,4}$	5.5423e–04 (0.8351)
π_{KK}	–0.2660 (0.0842)	$H_{2,5}$	3.5193e–04 (0.4324)
π_{KL}	0.2263 (0.0594)	$H_{3,6}$	4.8293 (1.7930)
π_{LL}	–0.2861 (0.3215)	$H_{4,7}$	1.7571 (0.9496)
π_0	4.3584E–03 (6.5663e–03)	$H_{5,8}$	0.7041 (0.2686)
$E_{2,1}$	–0.8166 (0.1039)	$H_{6,9}$	3.3614 (1.8105)
$E_{2,2}$	0.1925 (0.0882)	σ^2_u	4.28478e–05
$E_{3,1}$	1.5075 (0.2540)		

Table 10.2   Residual diagnostics: US macro model

	Equation			
	S_K	S_L	S_E	$\ln Q$
DW	1.7885	2.0268	2.1195	1.8892
Q(18)	23.2226	16.1559	17.0336	19.3560
	(0.1822)	(0.5817)	(0.5208)	(0.3702)
LM(1)	1.0211	2.0867	1.5877	1.6054
	(0.3122)	(0.1486)	(0.2077)	(0.2051)
t(43)	0.1950E–01	–0.2191E–01	0.1564E–02	0.2092E–01
	(0.9845)	(0.9826)	(0.9988)	(0.9834)

Notes: significance levels in parentheses. Tests are as follows:
DW   = Durbin–Watson test for first order serial correlation;
Q(18) = Box–Pierce *Q* test for general serial correlation/non-stationarity;
LM(1) = Breusch–Pagan Lagrange Multiplier Heteroskedasticity Test H1: $e_t^2 = f(t)$;
t(43)   = *t* test on residual sample mean H0: $E(e_t) = 0$.

manufacturing of 1.15 for a homogeneous function and 1.28 for a non-homothetic function, and Capalbo's (1988) estimate of 0.77 for the US agricultural sector. The parameters of the production function have the expected relationships. Increasing application of any factor leads, *ceteris paribus*, to diminishing and eventually decreasing returns. Also the second derivatives of the function are all positive within some range of input values. Increasing the use of other factors raises the marginal product of a factor of production. Table 10.2 presents the results of diagnostic tests on the residuals of each equation. The results show that the model is an adequate representation of the data for all the equations.

As seen from the estimates of the variances of the relevant disturbances (*H*), the labour and capital trends are integrated random walks as the variance of η_{Ai} is insignificantly different from zero. The energy trend is a local linear trend where both the disturbances have significant variances. Figure 10.3 presents the time paths of the technical change trends. Capital would be expected to have little trend, as the quantity of capital is theoretically the capitalized sum of capital services. This should hold as long as the government statisticians succeed in dividing changes in the nominal stock of capital between volume and inflationary components. However, as explained above in this model, there is also a factor-neutral technical change trend that has not been estimated. Therefore, we should assume that the general downward trend in the capital augmentation factor is due to a similar upward trend in the factor-neutral technical change trend. As a result of the high estimated degree of returns to scale, estimated overall technical change has been fairly
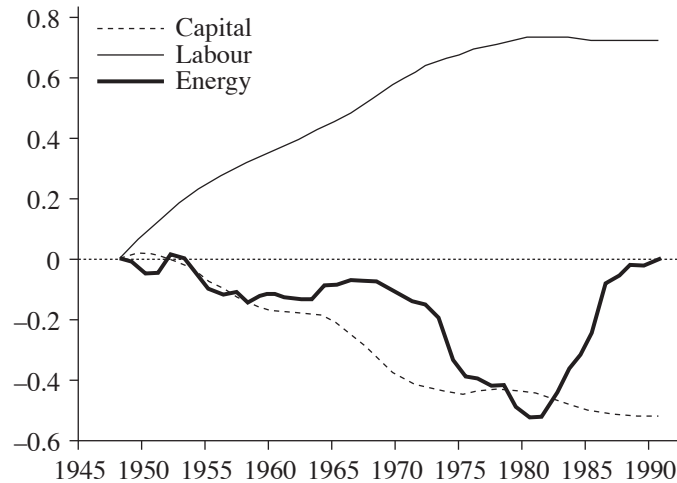
Figure 10.3   USA: factor augmentation trends

modest with around a 50 per cent increase in effectiveness over the period. The fluctuations in the trend would be partly due to changes in the capacity utilization of capital.

Relative to this overall trend, the efficiency of labour use has increased substantially over time. The rise in labour efficiency is expected given the high share of labour in costs, which would induce labour-saving technical change and higher levels of human capital accumulation over time.

Relative to the overall upward trend, energy shows large fluctuations. Until the mid-1960s autonomous energy efficiency is increasing and then it starts a sharp decline. However, the results show that the first oil shock in 1973 does not disrupt the overall downward trend in energy efficiency. Only after the second oil shock does the trend reverse and energy efficiency increase. Finally in the late 1980s the rate of improvement in autonomous energy efficiency slows as the price of oil again falls.

These results show that when the overall TFP trend is broken down into its component parts, technical change is shown to be a much more fragile and erratic process than is often assumed in the literature (for example Barnett and Morse 1963). The augmentation indices for different inputs may be moving in opposite directions and even change direction as in the case of energy here. At different points in time various of the alternative theories of the coupling and decoupling of energy use and GDP discussed above appear to explain the trend. The impression is of initial gains in energy efficiency that eventually 'run out of steam' due to the effects of rising personal energy consumption and lower marginal productivities of new energy applications as the price of

energy fell in the first three decades after World War II. The first oil shock was not significant enough to totally reverse that trend and even after the trend reversed it was not sustainable.

Rangelands in Botswana

Ecosystem stability and resilience are critical in the generation and maintenance of economic welfare. Current human activity, although aimed at increasing the productivity and stability of production of natural systems, may adversely affect the resilience of those systems and render them more susceptible to systemic shocks and stress. Declining resilience may mean that current human activity is unsustainable into the future.

Though some theoretical issues have been explored (for example Barbier 1993; Perrings et al. 1995), little progress has been made on empirical measurement. Naturally, the lack of data on environmental and biological variables is as much a constraint here as in any other area of natural resource economics (Conrad and Clark 1987). The generalized technological change approach could be valuable here as it can be used to estimate unobserved changes in the states of environmental variables that affect economic productivity. This approach is illustrated using a study of rangeland productivity in Botswana. The reader can find a description of the background to the case study and the rationale for the way the model is constructed in the paper we have already published on this topic (Perrings and Stern 2000). In this chapter, we therefore focus on describing the model and explaining the results.

It is assumed that the economy is made up of identical price-taking livestock farmers who enjoy open access to the range, and who maximize the utility derived from the profits, Π, from livestock production. The property rights regime is assumed to be essentially open-access, implying that there are no economic or social incentives for farmers to take the external costs of natural resource degradation into account in their stocking strategies. Although the introduction of boreholes is now introducing some private control over access to the range, the assumption is not unreasonable for the period being evaluated. Individual livestock farmers are, therefore, assumed to neglect the effect of their actions on the state of the range. Hence, the private decision problem is to maximize the utility of the net benefits of livestock production subject to the dynamics of the farmer's own herd. The short- and long-run dynamics of the range are assumed to be irrelevant to the private decisions of farmers. The only livestock to enter the farmers' profit function is cattle. Sheep and goats are excluded from the model, although they are very important in reality. They are assumed to be risk-averse. Risk-neutral models were tested, but performed extremely poorly. The general form of the model is given by the optimization

problem that follows. Pastoralists maximize the net present value of their welfare W over time:

$$Max_{Uit} W_{it} = \sum_{t=0}^{\infty} \rho^t W(\Pi_{it}) \tag{10.15}$$

subject to the following growth equation for their cattle herd:

$$\Delta X_{it+1} = X_{it} [\alpha_1 (1 - X_t/K_t) + \alpha_2 (s_t - 1)] - U_{it} + \varepsilon_{Xit} \tag{10.16}$$

where:

U_t	is herd offtake,
X_t	is the aggregate stock on the rangeland,
X_{it}	is the farmer's own herd,
K_t	is the state of the range,
s_t	is rainfall,
ρ	is the discount factor,
ε_X, η_t	are random error terms.

The period interval is a year starting in September. The animal stock variable is measured at the beginning of each time period, whereas the flow variables are measured for the duration of the time period. Peak rainfall occurs in summer (southern hemisphere). Animal growth depends on the state of K at the beginning of the time period, the rainfall within the period and offtake. Recent theories of rangeland dynamics argue that herd dynamics are most influenced by rainfall in years of exceptionally high or low rainfall and most influenced by stocking density in years of average rainfall (Arntzen 1994; Perrings 1994). Unlike Perrings (1994), we assume that rainfall only interacts with X_{it} and not with $X_{it} X_t/K_t$. This is because the functional form in Perrings (1994) implies that increases in rainfall reduce the growth of livestock when cattle exceed the current carrying capacity, which is counter-intuitive.

We assume that profits are given by:

$$\Pi_{it} = p_{Ut} U_{it} - C(X_{it}, Y_t, s_t) \tag{10.17}$$

where p_{Ut} is the price of cattle offtake. The net cost function, C_0, may be either positive or negative, since it admits the possibility that there may be stock benefits to livestock holdings. The function has the following form:

$$C(X_{it}, Y_t, s_t) = (\kappa_0 + \kappa_X X_{it} + \kappa_Y Y_t + \kappa_s s_t) X_{it} \tag{10.18}$$

where X_{it} is the cattle stock of herder i, Y_t is a measure of the non-farm costs or benefits of agriculture, and s_t is a measure of rainfall deficit (rainfall relative to

the mean over the sample period). The cost of holding livestock, κ_x, includes labour and material intermediate inputs. Labour costs of herding each additional animal are thought to decline initially with increasing herd size, but eventually to increase. The stock benefits of livestock are the sum of benefits derived from draft power, non-meat products, insurance against adverse climatic conditions and so on (Perrings 1996).

In the estimated cost function, Y_t is proxied by GDP per capita. This reflects two things. First, subsidies to agriculture are highly correlated with per capita GDP. Second, increased wealth increases demand for livestock – styled a 'sink for savings' by Collier and Lal (1984) – and raises the benefits of livestock holding. Rainfall is expected to reduce the cost of production through its impact on demand for supplementary feed, water and the like. This will vary with the size of the herd.

Utility of farmer i at time t, W_{it}, is given by the Box–Cox transformation utility function:

$$W_{it} = ((\Pi_{it})^\delta - 1)/\delta \qquad (10.19)$$

which allows us to estimate the degree of risk aversion reflected in the value of the parameter δ. For a risk averse farmer $\delta < 1$.

The growth of cattle herds is assumed to be a function of rainfall, a time trend, the average availability of graze and the area grazed. The latter is a function of the increase in the number of boreholes (tubewells) sunk over this period (Braat and Opschoor 1990). We therefore model the annual increase in grazing area as a function of the number of boreholes. There are two equations of motion describing range dynamics. The first (10.20) describes the dynamics of the current carrying capacity, K_t. The second (10.21) describes the dynamics of the long-run maximum carrying capacity or climax state, M_t.

$$\Delta K_{t+1} = K_t [\beta_1 (1 - K_t/M_t) + \beta_2 (s_t - 1)] - \mu \hat{X}_{t+1} + K_t \eta_t/M_t \qquad (10.20)$$

$$\Delta M_{t+1} = \frac{g_1 M_t/\hat{K}_{t+1}}{1 + \exp(g_2(1 + g_3 M_t/\hat{K}_{t+1}))} + \eta_t \qquad (10.21)$$

where:

$$\hat{K}_{t+1} = K_t [\beta_1 (1 - K_t/M_t) + \beta_2 (s_t - 1)] - \mu \hat{X}_{t+1} \qquad (10.22)$$

$$\hat{X}_{t+1} = X_{it} [\alpha_1 (1 - X_t/K_t) + \alpha_2 (s_t - 1)] - U_{it} \qquad (10.23)$$

and η is a random error term. The first of these equations is the more familiar, although it has some distinctive features. It assumes that the growth of graze and browse in any given period – and hence carrying capacity – follows a logistic path, in which the natural rate of regeneration varies with rainfall. The growth of graze and browse is also assumed to vary with consumption during the period. Since this includes consumption by calves and stock added during the period, it is described by the term μX_{t+1}.

The second equation of motion is less familiar. It does not derive from existing range ecology models, although it is intended to capture the sense of the informal state and transition models. Equation (10.21) describes the evolution of the long-run or potential carrying capacity of the range. M can be reduced when the current carrying capacity is less than a minimum proportion of the equilibrium value M. This use of the threshold level of $M_t/\hat{K}_{t+1}$ below which M is unchanged expresses the idea of a loss of resilience. The system is less resilient the further K is from M. The functional form used to transmit changes in K to changes in M is a smooth transition regression model (STR) (Granger and Teräsvirta 1993). $\Gamma = 1/(1 + \exp(\gamma_2 (1 + \gamma_3 M_t/\hat{K}_{t+1})))$ switches between 0 and 1 along a logistic curve as $M_t/\hat{K}_{t+1})$ increases. The error term η_t means that in the absence of such loss of resilience changes in M (and therefore K) are possible. These changes may reflect permanent expansion of grazing into new areas by the expansion of the number of waterholes but also temporary variations in the area grazed each year.

Perrings and Stern (2000) solve the optimal control problem to show that the privately optimal rate of offtake U_{it}^* is given by:

$$U_{it}^* = \frac{C_{it} + \left(\dfrac{\lambda_t}{P_{Ut}(1 + \alpha_1(1 - X_t/K_t) + \alpha_2(s_t - 1)) - \dfrac{\partial C}{\partial X_{it}}} \right)^{\frac{1}{\delta - 1}}}{p_{Ut}} \qquad (10.24)$$

We treat λ_{it} as an additional state variable estimated using the Kalman filter. It evolves deterministically according to:

$$\lambda_{it+1} = \left(\frac{1 + r}{1 + \alpha_1(1 - X_t/K_t) + \alpha_2(s_t - 1)} \right) \frac{\partial C}{\partial X_{it}} \, \Pi_{it}^{\delta - 1} + \lambda_{it} \qquad (10.25)$$

Equation (10.24) gives the privately optimal offtake for a single herd. Aggregating and adding a random error term, ε_{Ut}, we have

$$U_t^* = n_t \, U_{it}^* + \varepsilon_{\mathrm{U}t} \qquad (10.26)$$

where n is the number of herds.

This completes specification of the whole model. It consists of the two state space measurement equations (10.16) and (10.26); and the two transition equations (10.20), and (10.21).[11]

We estimate the initial state (K_1, M_1, λ_1) assuming that X and K are in a steady state and λ is at its (privately) optimal value. The first observation is not, however, used in the calculation of the likelihood function, which means that it is treated as a diffuse prior. The initial state covariance matrix is given by HH' where H is a 3 x 1 matrix, with $H_{11} = K_1 \, H_{21}/M_1$, $H_{31} = 0$, and H_{21} is estimated. The initial states are derived from (10.16), (10.20), and (10.21):

$$K_1 = -\,\alpha_1 \, X_1^{\,2}/(U_1 - \alpha_1 X_1) \qquad (10.27)$$

$$M_1 = -\,\beta_1 \, K_1^{\,2}/(\mu X_1 - \beta_1 \, K_1) \qquad (10.28)$$

$$\lambda_1 = (1 + r) \, p_{\mathrm{U}1} \, (p_{\mathrm{U}1} \, U_{i1} - C_{i1})^{\delta - 1} \qquad (10.29)$$

In order to identify K we set $\alpha_1 = 0.3$. This value is the same as in Perrings (1994) and is close to that (0.265) estimated in a linear regression of (10.16) assuming that K is constant. Because (10.16), (10.26) is a recursive system an additional identification restriction is required. We set the correlation between the error terms of the two measurement equations $\varepsilon_{\mathrm{x}t}$ and $\varepsilon_{\mathrm{U}t}$ to zero. $\sigma\varepsilon_{\mathrm{x}}$ is concentrated out of the likelihood function so that E_{11} is set to 1. This leaves 15 parameters to be estimated. Full details of the data employed are provided in Perrings and Stern (2000). In that paper we also conducted a number of policy experiments with the model that are omitted here.

Residual diagnostics for the measurement equations are given in Table 10.3. Both equations fit the data reasonably well. The residual diagnostic statistics are also encouraging.[12] The maximum likelihood estimates of the hyperparameters are given in Table 10.4. The standard errors are estimated using the Berndt et al. (1974) algorithm. Around half the estimated parameters have t-statistics greater than one. This implies that a more parametrically parsimonious model might be developed or optimally a longer time series is required to obtain more accurate parameter estimates. σ^2_u is the estimate of the standard error of the residuals in the cattle stock equation (10.16), which was concentrated out of the likelihood function. The other error variances involve this term so that for example the standard deviation of the residuals in the offtake equation (10.26) is $\sigma_u \, E_{2,2} = 0.001038$.

Figure 10.4 presents estimates of the variables that drive private stocking and offtake decisions: the price of offtake, the net cost of livestock holdings and the

Table 10.3   Residual diagnostics: Botswana model

	Equation	
	U_t	X_{t+1}
R^2	0.77721	0.99376
DW	1.426290	2.584818
Q(7)	13.778183	11.538466
	(0.05527020)	(0.11679514)
ADF	–4.18073	–4.06454
B–P	2.627091	6.947954
	(0.26886503)	(0.03099352)

Notes: significance levels in parentheses. Tests are as follows:
DW   = Durbin–Watson test for first order serial correlation;
Q(7) = Box–Pierce Q test for general serial correlation/non-stationarity;
ADF = Augmented Dickey–Fuller test for residual stationarity;
B–P = Breusch–Pagan test for coefficient variation.

Table 10.4   Maximum likelihood estimates of hyperparameters:
              Botswana model

Parameter	Estimate	Parameter	Estimate
α_2	0.13859	r	0.16501
	(0.05495)		(0.04824)
β_1	1.19394	κ_0	–0.04793
	(1.02271)		(0.08279)
β_2	0.61842	κ_X	0.0001514
	(0.48354)		(0.0006198)
μ	0.65206	κ_Y	0.01544
	(0.71201)		(0.00984)
γ_1	397.52479	κ_s	–0.01689
	(773.14788)		(0.00877)
γ_2	–181.89518	$E_{2,2}$	0.62907
	(369.21253)		(0.25000)
γ_3	–1.25890	$H_{2,3}$	13.96006
	(12.04458)		(8.38597)
δ	–0.48003	σ_u	0.00165
	(0.83499)		

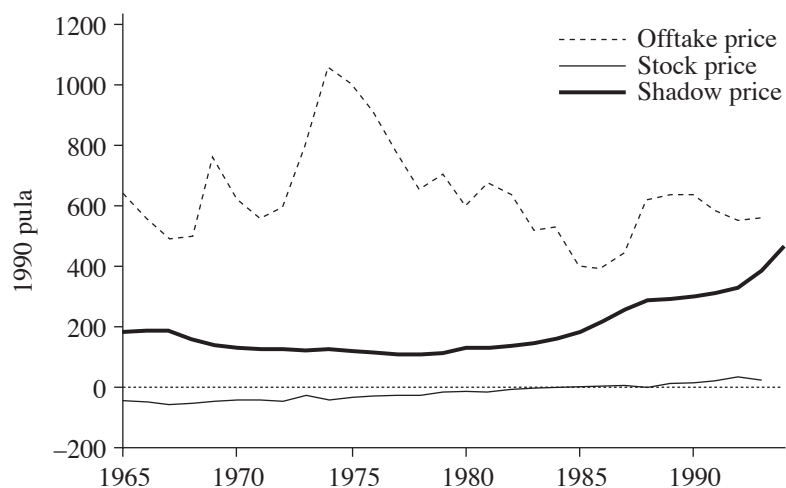*Note*:   Figures in parentheses are standard errors.

Figure 10.4   Livestock prices

private user cost of herd growth. The net cost of livestock holdings is initially negative, implying that there were net private benefits to holding cattle stocks (draft power, non-meat products, tax advantages and so on dominated the cost of herd maintenance). The relative value of the private benefits of offtake and live-stock holdings is summarized in Figure 10.5. In the late 1960s and early 1970s, the net benefits of livestock holdings were about equal to offtake benefits. This
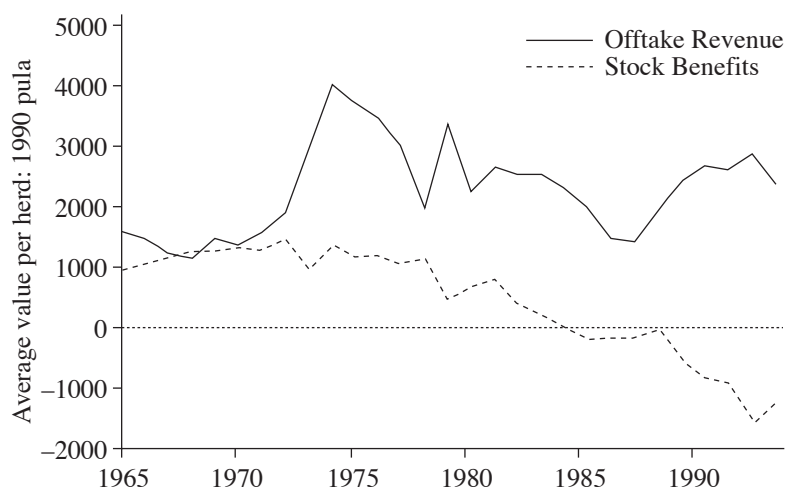
Figure 10.5   Livestock cost and offtake revenue (average herd)

might be expected from the literature on cattle herding in sub-Saharan Africa. But from the mid-1970s on, stock benefits declined as the opportunity cost of agricultural labour rose, becoming negative in the mid-1980s.

The parameter estimates for the cattle stock equation imply that, given the state of the range, rainfall in the current year has only moderate effects on the herd. The estimated parameter of 0.1389 is close to the OLS estimate of 0.125. The parameter estimates for the range transition equation imply that the intrinsic growth rate is 1.19394. The growth of the carrying capacity of the range fluctuates strongly with current rainfall. The grazing coefficient is 0.65206. All these coefficients are higher than we previously supposed (Perrings 1993, 1994). The estimated initial values for K and M are 2.29 million and 3.48 million, respectively, implying that X was at 59 per cent of K and K at 66 per cent of M. That is, initial stocking rates were above the maximum sustainable yield (given water availability in 1964/65).

The parameters of the cost function show evidence of decreasing returns to scale. There are net benefits for small herds when national income is low. At the average GDP per capita for the period, net stock benefits peak for a herd of 22 animals, while stock costs exceed stock benefits for herds of greater than 44 animals. At 1965 income levels net stock benefits peaked at a herd size of 120. It would thus appear that economic development has reduced the net benefits from stockholdings. This may be because it has raised the opportunity cost of labour used in herding or because use of cattle for non-consumption purposes such as draft power has fallen.

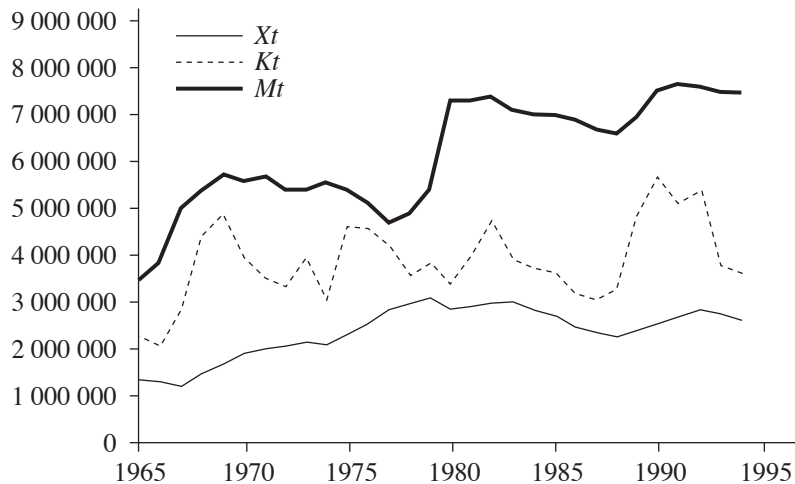Figure 10.6 shows the evolution of the state variables over time. These

Figure 10.6   State variables

include both the two unobserved variables estimated by the Kalman filter, and the cattle stock. The stocks are the relevant quantities at the beginning of the years shown: that is X_{1994} is the cattle stock at the end of 1993. The trend in the time series for M is a function of the spread of boreholes. That is, the maximum carrying capacity of the range increased with the supply of water for livestock. Our results show that this expansion is not uniform. There are substantial increases in M during periods when the cattle herd approached current carrying capacity and some consolidation in the intervening period. But we cannot tell if the decline in M in those periods is due to change in the area grazed or due to a slow degradation of the rangeland that is not associated with loss of resilience. The current carrying capacity K shows large fluctuations as would be expected from the high estimates we obtained for the parameters in its equation of motion. The cattle stock never actually exceeds the estimated carrying capacity.

Figure 10.7 decomposes the changes in M into random fluctuations and the contribution of the parametric loss of resilience function. The changes are in terms of $\bullet M_{t+1}$ so that the changes occurring in the years indicated result in the increase or decrease in M in the following year. The results indicate one potential loss of resilience event in 1985–1986 (contributing an 8 per cent reduction in M going into 1986/87). However, as the parameters γ_1, γ_2, and γ_3 are statistically insignificant, we are unable to confirm a loss of resilience. M itself declines by only 3.7 per cent between 1985/86 and 1986/87. This may have been due to expansion into new grazing areas occurring simultaneously with
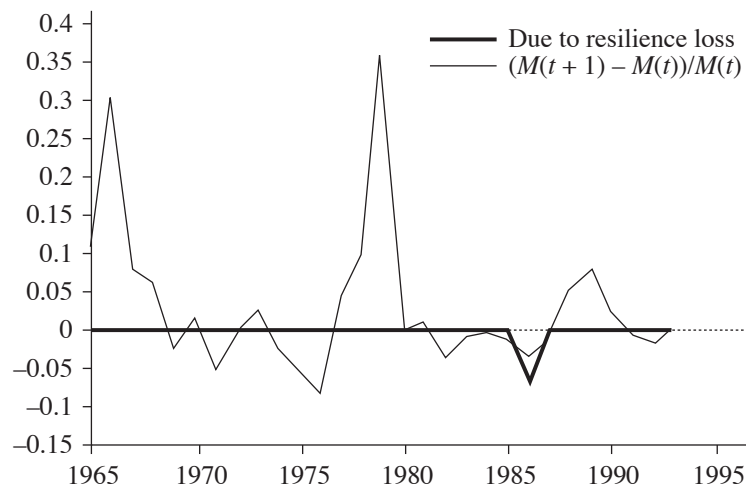

Figure 10.7   Decomposition of climax state M into random fluctuations and loss of resilience function

the loss of resilience in some areas of the rangeland. These kind of potential responses make determining whether a loss of resilience has occurred from aggregate data of the sort we use here particularly difficult.

These episodes are a response to rainfall deficit shocks, and occur when the system is stressed due to high grazing pressure. 1985/86 was the fifth year of a major drought. Rainfall was actually slightly higher than in the previous year, but the cumulative effects of drought worked to lower current carrying capacity relative to the size of the herd. *X/K* is at a maximum for the entire sample in 1985/86. They also work to reduce K_{t+1}/M_t, the variable that actually controls the loss of resilience switch in our model. This is at a minimum in 1985/86. The large coefficients for the transition equation for *M* imply that the resilience threshold is very sharp.

We are interested in whether it is possible to detect change in the capacity of the system to absorb exogenous shocks (the measure of resilience *sensu* Holling 1986). The changing sensitivity of the system to rainfall shocks is illustrated in Figure 10.8. This shows the threshold level of rainfall that we estimate to have been sufficient to induce a loss of resilience compared to actual rainfall. This was derived using a one-step ahead simulation – that is lagged values of variables are actual observations not simulations and the error terms from the econometric model are treated as exogenous variables. Changes in rainfall affect *M* by affecting the optimal offtake, the growth of the herd and the growth of the range. The optimal offtake impacts on $\hat{X}_{t+1}$ in addition to the direct rainfall affect on $\hat{X}_{t+1}$ which then affects $\hat{\kappa}_{t+1}$ in addition to the direct rainfall affect
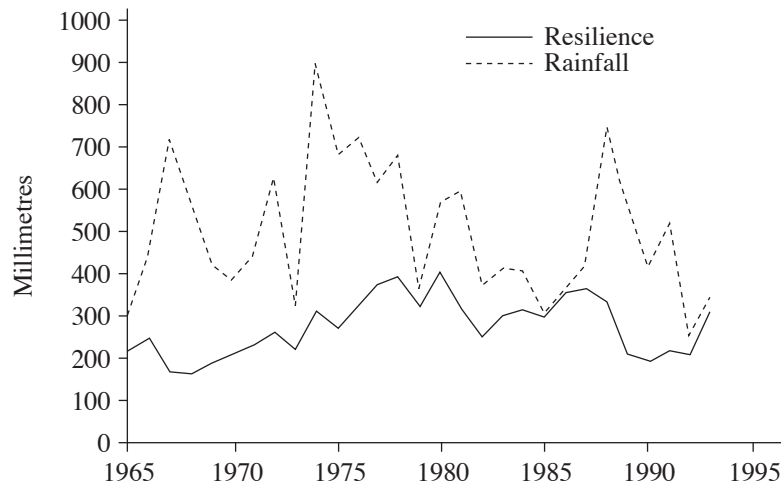

Figure 10.8   Resilience with respect to rainfall

on $\hat{K}_{t+1}$. $\hat{K}_{t+1}$ alone then enters the loss of resilience function. We then perturb actual rainfall until $\Gamma = 1/(1 + \exp(\gamma_2 (1 + \gamma_3 M_t/\hat{K}_{t+1}))) = 0.5$, that is halfway switched on. This rainfall figure is the reported 'resilience' in Figure 10.5. The dating is the same as in Figure 10.4 so that rainfall would have to be 360 millimetres and below in 1986 to cause a loss of resilience that would result in M declining from that year to 1987. The link between change in the resilience of the range and herd size is complicated by the fact that there was extensive growth of the livestock sector in the period. More range was brought into use. As a result, resilience is not a monotonically decreasing function of herd size. Nevertheless, it does turn out that the system came closest to losing resilience in 1979, when the size of the national herd was at its highest.

The implications of this for the speed of return to equilibrium are illustrated in Figures 10.9 and 10.10. These report a sequence of impulse responses of K and X to a change in rainfall. The responses are measured in LSUK/millimetre of rainfall (thousand livestock units per millimetre of rainfall). The graphs show the one-, three-, five- and ten-year responses to a change in rainfall in the year on the X axis. The impulse response function is not shown in other years for simplicity. As this is a non-linear model the impulse response function is different for a perturbation in each of the years in the sample. Range vegetation is inherently more responsive to rainfall fluctuations than livestock, as is to be expected. This is partly because of the grazing term. Growth of the vegetative cover of rangeland slows as cattle stocks build up in wet periods. The higher the figure the larger the movement for a given shock and the more 'unstable' or responsive is the system.
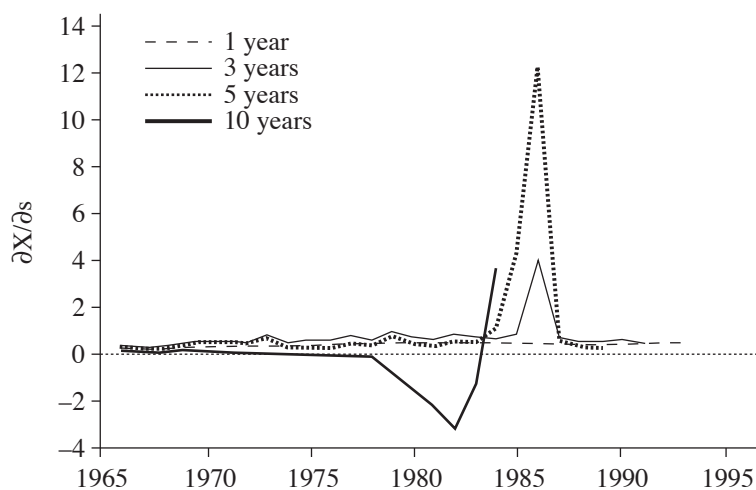

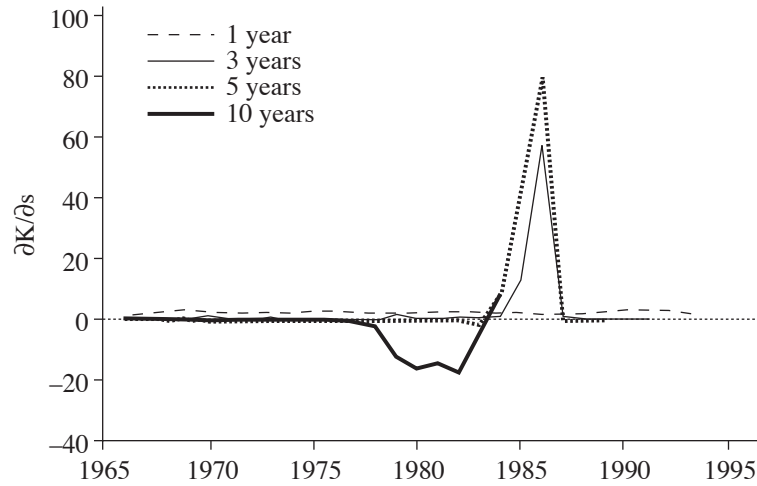*Figure 10.9   Response of cattle stock to rainfall*

Figure 10.10   Response of rangeland to rainfall

The one period impulse responses of the two variables are generally opposite; that is the responsiveness of K increases as that of X decreases. X is strongly influenced by the effect of rainfall on offtake. Higher rainfall reduces offtake, spurring the growth of X, and vice versa. As grazing pressure rises in droughts, the growth rate of X slows down for any given level of rainfall. Overall, though, the one period responsiveness of both livestock and vegetation to variations in rainfall rises over the period. That is, the reduction in resilience of the system implies an increase in its volatility. It takes a progressively smaller change in rainfall to induce the same response in both vegetation and livestock. In general, K is more responsive to rainfall shocks than X, but the nature of the response varies over the period. Up until the late 1970s, the immediate rangeland response to rainfall is typically substantial, but dies out fast. The return time to the previous equilibrium involves a period of between three and five years. By contrast, the cattle stock initially responds slowly. The effects of a shock build up over three to five years and the return time to equilibrium takes a much longer period – typically exceeding 10 years. From the late 1970s on, however, the pattern changes. The return time for rangeland increases until it, too, exceeds 10 years. In the mid-1980s, drought, the loss of resilience in K is reflected in a very sharp increase in the impulse response over all but the very short period. By the late 1980s, the response to rainfall shocks is again a decreasing one as the system converges on a new equilibrium.[13] The general pattern of the impulse responses of X is similar. In the mid-1970s, during a period of high rainfall, the maximum response of cattle stocks to rainfall shocks

occurs in one year. By the early 1980s, however, the position is reversed. The 10-year response is equivalent to four times the one-year response; while in 1985 the ratio rises to about seven to one. That is, consistent with a loss of resilience, the effect of a rainfall shock in those years is explosive, rather than damped.

CONCLUSIONS

In this chapter we have argued that an alternative tractable way of estimating changes in environmental and natural capital stocks is to treat the impact of those changes on the economic system in the same way as econometricians have traditionally modelled the effects of unobserved changes in technology on economic output. This idea is derived from Perrings (1987) and O'Connor's (1993) conception of change in the economy-environment system as a process of uncontrolled technological change.

The US case study illustrates what it is possible to do with sophisticated time series techniques in the arena of the conventional modelling of technological change. In particular, a time-varying estimate of the unobserved autonomous energy efficiency trend was extracted from the US macro data using a simple optimization model of economic behaviour and a simple structural time series model of technological change estimated with the Kalman filter.

The Botswana study is both interdisciplinary and integrated. Insights from ecology are combined with economic intertemporal optimization theory in a form relevant to the particular institutional conditions of Botswana. The Kalman filter is again used to estimate a model that jointly includes parameters of the economic system such as risk aversion and the discount rate and the unobserved state variables of the natural system – the current and equilibrium states of the rangeland. These estimates are extracted from the data containing minimal information about the natural system – the number of cattle and level of rainfall each year and the number of tubewells as a proxy for the area grazed.

It seems that many such similar integrative ecological-economic applications could be developed to model integrated systems for which we have limited measurements of the relevant natural capital variables. The technique might also be extended to investigate pure natural science problems. A step in this direction is provided by Stern and Kaufmann (2000) in a model of global climate change. Further development of such a model could include modelling unobserved time series such as stored ocean heat, which plays a similar role in the climate system that renewable natural capital stocks do in ecological-economic systems.

NOTES

1. A stationary variable has constant mean and variance. Classical regression methods and inference are only applicable to stationary variables. If the variables are non-stationary, standard regression results may indicate that there is a significant relation between the variables when in fact none exists – a so-called spurious regression (Granger and Newbold 1974). But in some cases the non-stationary components of a number of time series are shared so that a linear combination of the series is stationary. This phenomenon is called cointegration. When the variables cointegrate, valid inference is possible in regression models.

2. Stern (2000) examines the US macro data using cointegration modelling. The implication of the latter results is that a linear combination of the stochastic trends estimated in the model in this chapter cointegrate – in other words, the linear aggregate is a stationary variable.

3. Simple measures of energy efficiency divide GDP by energy used and hence require no econometric estimation. Autonomous energy efficiency refers to changes in the effectiveness with which energy is used holding the effective units of the other inputs constant. Only econometrics can provide estimates of this trend at the macroeconomic level. At the micro-level engineering based studies can also be used.

4. Equation (10.1) can be obviously generalized to multiple outputs. A useful simplifying assumption is that the production function exhibits constant returns to scale in all inputs including the resource inputs. This implies that there are decreasing returns when more inputs are applied to a given resource stock R. Again, generalizations can be made. If N is measured in terms of rainfall, temperature and so on, rather than water, heat and so on, the relevant constant returns relates to the expansion of X and R but not N.

5. Stern (1999b), in an empirical study of US agriculture, shows how non-comprehensive measures of MFP – that is the traditional Barnett and Morse unit cost and energy cost are strongly affected by changes in the prices of other inputs in a way that obscures the long run trend in resource quality and availability. See also Cleveland and Stern (1993) for a discussion of alternative indicators in US forestry. Mattey (1990) shows that stumpage prices are an ineffective indicator of resource scarcity in forestry.

6. The simplest type of stochastic trend is a random walk. The current value of a random walk is equal to the previous value plus a random shock and perhaps a constant or drift term. This means that the stochastic trend has a different value in every time period. If we attempted to estimate this model using classical linear regression, we would have more parameters to estimate than observations to estimate them with. Therefore, the model cannot be estimated using regression methods. But using the Kalman filter only the variance of the shocks and the value of the drift constant – two parameters – need to be estimated using maximum likelihood methods. Given these estimated hyperparameters, the Kalman filter algorithm computes the value of the stochastic trend in each period given the observed data. In the US model the stochastic trends are modelled using a local linear trend model, which is a random walk where the drift term is itself a random walk. The Botswana model has more complex non-linear stochastic trends.

7. We can assume that in the macroeconomy, the quantities of factor inputs are exogenous at least in the short run, but that factor prices are endogenous. This obviously is not strictly true, especially for energy prices. However, it is a more reasonable assumption for the macroeconomy than for a single industry or firm. Also, we should expect the production technology at the macroeconomic level to be non-monotonic. This is because the assumption of free disposal may no longer hold (Stern 1994).

8. This means that the estimate of autonomous energy efficiency is not absolute but relative to overall technical progress.

9. De Jong's diffuse Kalman filter algorithm avoids the need to specify initial conditions for non-stationary stochastic trends but it can only handle models that are linear in the state variables. This is also the reason why homogeneity of the production function is assumed.

10. This approach was used by Berndt et al. (1993).

11. Note that although the cattle stock is a state variable in the private decision problem, it is an observation in the Kalman filter estimation.

12. Neither Durbin–Watson statistic shows definite evidence of first order serial correlation. The Box–Pierce Q statistics present a similar picture. There are no tabulated significance levels for the augmented Dickey–Fuller statistic in a non-linear model of this type but these statistics would indicate reasonable residual stationarity if these were linear regressions. The Breusch–Pagan test for coefficient variation shows that the Kalman filter model is picking up most of the coefficient variation that is present, although the statistic for the $Xt + 1$ equation is significant at the 5 per cent level but not at the 1 per cent level.
13. Note that the effects of the 1992 loss of resilience do not show up in Figure 10.6 as there are only two periods remaining in the sample.

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