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Regime shifts and technology diffusion in crop yield growth paths with an application to maize yields in Zimbabwe

Robert J. Myers and Thomas Jayne*

An alternative specification for the trend component of crop yield growth is developed and applied to maize yield data for Zimbabwe's large-scale farming sector. This accounts for permanent regime shifts as new technologies are discovered but allows gradual absorption as adoption follows a diffusion path. Econometric methods are used to estimate the timing and importance of innovations, as well as the length of the diffusion path. Results from an application to Zimbabwe commercial maize yields indicate two major regime shifts that can be associated with the introduction of hybrid seed varieties, and a diffusion path that extends over a decade.

Crop yield time series are often modelled as the sum of two components – a trend process representing improvements in seed varieties, increased fertiliser use, better management practices etc. and a stationary process representing transitory deviations around trend caused primarily by weather. Both components are of interest to economists and policy-makers. The trend component can be interpreted broadly as improvements in technology, so that modelling the trend characterises the rate of technological advance. The stationary component accommodates much of the short-term risk inherent in crop yield distributions, and so can be a useful input into farm decision analysis, crop insurance rating and the pricing of yield futures and options.

Early models of crop yield growth used deterministic trends in the form of linear or higher-order polynomial functions of time (e.g. Thompson 1969; Menz and Pardey 1983; Gallagher 1986). It soon became apparent, however, that polynomial trends are not adequate for capturing trend yield growth. Polynomial trends assume the trend component of yield grows at a very

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* Robert J. Myers, Associate Professor and Thomas Jayne, Visiting Associate Professor, Department of Agricultural Economics, Michigan State University, East Lansing, MI, USA. The authors would like to thank Joseph Rusike for supplying the data and sharing his knowledge of the Zimbabwe maize research and seed industries. Acknowledgement is made to the Michigan Agriculture Experiment Station for its support of this research.

smooth (and often linear) rate which is completely predictable. In reality, trend yield growth tends to be somewhat erratic and lumpy as new technological innovations come on line at random intervals (Moss and Shonkwiler 1993).

Stochastic shocks to trend yield growth rates can be captured using a stochastic trend model (Harvey 1985; Stock and Watson 1988). In this case, the trend component of yields increases by a fixed amount on average, but in any given period the change in the trend deviates from the average by some random unpredictable amount. Positive shocks indicate an above average level of technological innovation while negative shocks indicate a below average level. Stochastic trend models imply that future yield growth paths are much more difficult to predict than in the deterministic trend case, and have been used successfully by a number of researchers to characterise trend and stationary components of US corn yields (Fackler 1989; Kaylen and Koroma 1991; Moss and Shonkwiler 1993). In particular, Moss and Shonkwiler (1993) get a very good fit to historical US corn yields by incorporating a stochastic trend and using an inverse hyperbolic sine transformation to model nonnormality in the stationary deviations around trend.

A problem with modelling technological innovations in crop yield growth paths with a standard stochastic trend approach is that the stochastic trend does not account for well-known features of the way technological change diffuses through the farm sector. The effect of shocks to a standard stochastic trend are both immediate and permanent, implying that when a technological innovation occurs it is immediately and simultaneously adopted by all farms. It is well known, however, that technological improvements are typically adopted slowly at first with a small number of early innovators followed by a period of rapid adoption, and then final adoption by a small group of laggards. This S-shaped diffusion pattern implies that, rather than having frequent technological innovations whose permanent impacts are felt immediately, the trend component of crop yields might be better characterised by less frequent but larger innovations representing particular regime shifts in crop yield growth paths. These regime shifts result from major technological innovations whose effects are spread over time as they diffuse through the farm sector.

The purpose of this article is to present an alternative specification for the trend component of crop yield growth which accounts for regime shifts and technology diffusion. The specification is similar to that in Lippi and Reichlin (1994) in that technological innovations have permanent effects that are absorbed gradually, and diffusion follows an S-shaped pattern. However, we allow for regime shifts which help identify the effects of specific technological improvements, such as a package of management practices, seed, and fertiliser use associated with the introduction of hybrid seed. The advantages of this regime shift-diffusion model are that it allows the length of the diffusion path to be estimated from data, and it also provides empirical results on the relative contribution of different technological packages (regime shifts) to trend growth in crop yields. It also may lead to quite different conclusions about the path of trend yield growth, and hence the distribution of stationary deviations around trend, compared to those obtained from the standard stochastic trend model.

The regime shift-diffusion model is applied to time series data on maize yields in Zimbabwe's large-scale farming sector. Results provide an estimate of the 'depreciation rate' in maize yields (the rate at which trend yield declines in the absence of major new technological innovations). Results also provide an empirical estimate of trend yield response to two major regime shifts associated with the introduction of hybrid seed varieties, and of the speed at which these technological innovations have diffused through the large-scale farming sector.

The next section summarises standard stochastic trend models of crop yield growth and highlights some of their advantages and disadvantages. Then the regime shift-diffusion model is introduced and applied to maize yields in Zimbabwe's large-scale farming sector. The concluding section assesses the potential usefulness of this new approach to modelling crop yield growth paths.

1. Stochastic trend models

Let y_t represent the logarithm of crop yield at time t and suppose that y_t can be decomposed into two components:

$$y_t = \tau_t + \varepsilon_t \tag{1}$$

where τ_t is a trend component and ε_t represents stationary deviations around trend. In the standard stochastic trend model τ_t is given by:

$$\tau_t = \tau_{t-1} + \eta_t \tag{2}$$

where μ is the drift (average trend growth rate) and η_t is a serially uncorrelated random shock to the trend satisfying $E(\eta_t) = 0$ and $E(\eta_t^2) = \sigma_\eta^2$.

The trend component τ_t is presumably driven by technological innovations such as improved seed varieties, better management practices, changes in fertiliser use, etc. while the stationary component ε_t is determined primarily by weather fluctuations. It should be clear that τ_t depends on farmer decisions regarding technology adoption and management practices, as well as private and public investments in agricultural research, extension, and marketing infrastructure.

In the stochastic trend models of Kaylen and Koroma (1991), and Moss and Shonkwiler (1993), the drift term μ is also allowed to change according to:

$$\mu_t = \mu_{t-1} + \xi_t \tag{3}$$

where ξ_t is a serially uncorrelated random shock satisfying $E(\xi_t) = 0$ and $E(\xi_t^2) = \sigma_\xi^2$. However, empirical estimates of σ_ξ^2 tend to be very small, indicating the assumption of $\sigma_\xi^2 = 0$ is reasonable in most cases.[1] Hence, we focus on the standard stochastic trend model (1) and (2).

The stochastic trend model allows a linear deterministic trend as a special case. To see this, let $\sigma_\eta^2 = 0$ so that repeated substitution of (2) into (1) gives:

$$y_t = \tau_0 + \mu t + \varepsilon_t \tag{4}$$

The initial trend value τ_0 takes the role of a constant and the trend component of y_t increases by μ every period, and is therefore completely smooth and predictable. This has obvious limitations for modelling crop yield growth.

In the more general case of $\sigma_\eta^2 > 0$ then τ_t increases by μ on average but the increase is also subject to a random shock η_t. We can think of η_t as a shock to the rate of technological innovation. Large positive values of η_t indicate an unusually high rate of yield growth while large negative values of η_t indicate an unusually low rate. Notice, however, that μ and the random shock η_t both have immediate and permanent effects on τ_t. Thus, technological innovations are implicitly assumed to be immediately and simultaneously adopted by all farms. Furthermore, the trend growth rate $\Delta\tau_t$ is assumed to be drawn from a fixed probability distribution with mean μ and variance σ_η^2. Thus, there is no possibility of regime shifts – a small number of major innovations which occur infrequently but shape yield growth over subsequent decades.

The stochastic trend model can be estimated using Kalman filter and maximum likelihood methods (see Harvey 1985; and Moss and Shonkwiler 1993) and has been shown to be quite effective in explaining crop yield movements over time. However, the standard stochastic trend model does not account for diffusion of technological innovations over time, which is a key component of the actual process of technological advancement in agriculture.

[1] $\sigma_\xi^2 > 0$ would imply that y_t has to be differenced twice to induce stationarity.

2. Regime shifts and technology diffusion

There is already considerable evidence available on technology diffusion in agriculture (Griliches 1957; Knudson 1991; Leathers and Smale 1991). While the diffusion path generally follows an S-shaped pattern, substantial variation can exist in the length and shape of the process. Indeed, the shape and duration of the diffusion process can be viewed as a function of numerous technological and institutional factors which interact in a complex manner and are difficult to determine *a priori* (Johnson 1969). It is also important to distinguish between technology generation and technology adoption. Productivity growth occurs only after adoption takes place and the length and shape of the diffusion process are contingent on the performance of input and output markets, extension systems and investments in infrastructure, in addition to plant breeding (Antle 1983; Binswanger and Pingali 1989; Evenson and Kramer 1988). Diffusion of improved seed varieties has often required increased use of other inputs, such as fertiliser, chemicals, and water control, to be economically viable. Thus, it is an oversimplification to equate technology diffusion with the proportion of farms using an improved seed variety.

The stochastic trend model can be generalised to account for two stylised facts about crop yield growth, namely, technological change may be driven by large infrequent innovations, leading to regime shifts in crop yield growth paths, and diffusion of technological innovations takes time and follows an S-shaped pattern. To accomplish this, suppose we continue to think of crop yields being comprised of the sum of trend and stationary components, but now specify the trend component as:

$$\tau_t = \tau_{t-1} + \mu + a(L)\sum_{i=1}^{n} \beta_i d_{it} + \eta_t \tag{5}$$

where the d_{it} are indicator variables satisfying $d_{it} = 1$ if technological innovation i occurs at date t and $d_{it} = 0$ otherwise; and $a(L)$ is a polynomial in the lag operator L representing the technology diffusion path. The diffusion path satisfies $a(1) = 1$ so that β_i represents the total contribution of innovation i to trend yield growth and $a(L)$ determines how this total contribution is spread over time. The trend is still subject to an underlying average growth rate μ in the absence of technological innovations d_{it}, and to random shocks η_t to that underlying growth rate. However, technological innovations d_{it} and their associated diffusion path $a(L)$ can now also influence trend yield growth. As in Lippi and Reichlin (1994), this specification of the trend component allows for autocorrelation in trend growth rates which is presumably driven by technology diffusion. However, Lippi and Reichlin model this autocorrelation by allowing the effects of random shocks η_t to diffuse over time (without regime shifts), while we model it by allowing regime shifts that follow a diffusion path.

The shape of the diffusion path $a(L)$ is critical to analysis of the regime shift-diffusion model. As pointed out by an anonymous reviewer, any $a(L)$ which is nonnegative and unimodal will generate an S-shaped diffusion path. Furthermore, data on crop yields alone are not going to be very informative about the parameters in $a(L)$ without additional restrictions. The number of lags in $a(L)$ may be quite large for long diffusion processes, making it difficult to estimate an unrestricted lag structure. Furthermore, if different regime shifts were allowed to have different diffusion paths, then the model would become essentially unidentifiable as regime shifts and diffusion rates could not be separated.

To overcome these problems we impose restrictions on the diffusion path. First, we assume each regime shift has the same diffusion path, so that there is only one $a(L)$ to be estimated. Second, we assume that $a(L)$ takes the form:

$$a(L) = \alpha \sum_{j=0}^{m-1} (1 + 5j)L^j/(1 - \delta L) \tag{6}$$

where $0 \leq \delta < 1$ and $m > 1$. The restriction $a(1) = 1$ then requires that:

$$\alpha[m + 5m(m-1)/2]/(1 - \delta) = 1 \tag{7}$$

Each $a(L)$ coefficient a_j represents the fraction of β_i which is absorbed at $t + j$. Thus, the path of cumulative increases in trend crop yield (the diffusion path) is found by summing the $a(L)$ coefficients from zero through to j. This diffusion path follows the specification in Lippi and Reichlin (1994).

There are several points to notice about the Lippi and Reichlin diffusion path given in (6) and (7). First, the specified lag structure is nonnegative and unimodal so it imposes an S-shaped diffusion path. Second, while the shape of the diffusion path is determined completely by the assumed form for $a(L)$, the length of the path is flexible and determined by the values of m and δ. Thus, we are imposing a particular shape on the diffusion path but allowing the data to determine its length. Other possible specifications for $a(L)$ could have been investigated (e.g. inverted-V, triangular, gamma distributed lag, or exponential lag). However, the Lippi and Reichlin lag structure is simple, parsimonious, and imposes a diffusion path shape that is consistent with prior knowledge about the way technological innovations diffuse through the agricultural sector. It also has the advantage that the length of the diffusion process does not need to be specified *a priori*, and so can be inferred from the data. For these reasons, the Lippi and Reichlin specification is used throughout the remainder of the analysis. It should be remembered, however, that imposing the Lippi and Reichlin lag structure (or any other lag structure) is really a form of identification restriction which makes the interpretation of the regime shift effects conditional on that particular specification for the shape of the diffusion path.

The regime shift diffusion model given by (5) through (7) represents a clear generalisation of existing crop yield growth models. Each indicator variable models a regime shift in the crop yield growth path. When regime shift i occurs ($d_{it} = 1$) a part of its permanent contribution β_i is felt immediately but the remainder is spread out over time, with the length and pattern of the diffusion determined by $a(L)$. If $\beta_i = 0$ for all i then there are no regime shifts and the model reverts to a standard stochastic trend model (1) and (2). If, in addition to $\beta_i = 0$ for all i, the shock to the trend has zero variance, $\sigma_\eta^2 = 0$, then the model reverts to the standard linear trend model (4). It is also possible that regime shifts occur, $\beta_i > 0$ for some i, but that the shock to the trend still has zero variance $\sigma_\eta^2 = 0$. In this case the trend component is determined completely by the constant growth rate μ and regime shifts d_{it} (i.e. yields are stationary around a linear trend with regime shifts).

The average growth rate μ has an interesting interpretation in the regime shift-diffusion model. If $\mu < 0$ this would indicate a constant 'depreciation rate' caused by lost resistance to pests and diseases, reductions in soil quality under continuous cropping and movement onto marginal lands, etc., in the absence of major new technological innovations. If $\mu > 0$ this would indicate a constant 'appreciation rate' caused by continual small improvements to existing technologies and practices in the absence of major new technological innovations.

3. Estimation

Estimation of the regime shift-diffusion model depends critically on the value of σ_η^2. As stated earlier, if $\sigma_\eta^2 = 0$ then crop yields y_t are stationary around a linear trend with regime shifts, and the trend component of crop yields can be viewed as deterministic for estimation purposes. In this case, repeated substitution of (5) into (1) gives:

$$y_t = \tau_0 + \mu t + a(L) \sum_{i=1}^{n} \beta_i x_{it} + \varepsilon_t \tag{8}$$

where $x_{it} = \sum_{j=1}^{t} d_{ij}$ is the accumulated history of d_i values up until date t. Equation (8) is similar to Perron's (1989) 'crash model' which allows for a single exogenous shock to the intercept in a linear trend model. Here, however, we allow for multiple shocks and include a diffusion path to determine how the effects of the shocks are spread over time.

Assuming $\sigma_\eta^2 = 0$, and that the indicator variables d_{it} representing technological innovations are known exogenous events, equation (8) is easy to estimate using maximum likelihood methods. The estimation equation is nonlinear in the parameters of $a(L)$ but estimation is still straightforward once a suitable distributional assumption has been made on ε_t. If ε_t is autocorrelated, then we can use an ARMA specification to model that autocorrelation and proceed with maximum likelihood estimation.

If the number and timing of the technological innovations d_{it} are not known *a priori* then a grid search procedure could be used to infer from the data the most likely dates that regime shifts occurred. Suppose initially that we know the number of regime shifts (major technological innovations) but not when they occurred. Then we could undertake a discrete likelihood search over all possible combinations of dates over which the regime shifts could have occurred, and pick the combination of dates which generate the highest likelihood value for the equation (8). This would provide the most likely dates for a given prespecified number of regime shifts to have occurred. To infer the actual number of regime shifts from the data we repeat this grid search procedure for every one of $i = 1, 2, \ldots, n$ regime shifts where the maximum possible number n is chosen based on data considerations, as well as knowledge of the technology adoption process for the particular application under study. Then, having chosen the most likely dates for $i + 1$ regime shifts, this model could be tested against the most likely dates for i regime shifts using a likelihood ratio test. This process could then be repeated sequentially testing for a smaller number of regime shifts until a final model is chosen and both the number and timing of regime shifts have been inferred from the data. Clearly, there are bounds on the maximum number n of regime shifts that can be accommodated in this grid search procedure because the number of nonlinear models that must be estimated expands rapidly as the sample size increases and the number of regime shifts allowed is raised. However, prior information on the technology innovation and adoption process for a particular empirical application may be used to reduce the size of the search by eliminating highly unlikely dates and combinations from the grid on *a priori* grounds.

If $\sigma_\eta^2 > 0$ then crop yields y_t are nonstationary with regime shifts d_{it} in the rate of drift, and the trend component of crop yields must be viewed as stochastic for estimation purposes. In this case, taking first differences of (1) and substituting (5) gives:

$$\Delta y_t = \mu + a(L) \sum_{i=1}^{n} \beta_i d_{it} + \mu_t \tag{9}$$

where $\Delta y_t = y_t - y_{t-1}$ and $\mu_t = \eta_t + \Delta\varepsilon_t$. If η_t and ε_t are independent (a reasonable assumption for crop yields), and ε_t is serially uncorrelated, then μ_t has a nonzero first-order autocorrelation and all other autocorrelations equal to zero. Hence, μ_t has a representation $\mu_t = e_t + \theta e_{t-1}$ for a serially uncorrelated sequence e_t satisfying $E(e_t) = 0$ and $E(e_t^2) = \sigma_e^2$. If ε_t is autocorrelated (but still independent from η_t) then μ_t would be a higher order stationary ARMA process whose representation depends on the autocorrelation structure of ε_t.

The first difference equation (9) is also nonlinear in the parameters because of the diffusion process $a(L)$ and the possible ARMA model for μ_t. However, the model can be estimated easily using maximum likelihood methods after making a suitable distributional assumption on μ_t. If the indicator variables d_{it} are known exogenous events then estimation proceeds in the usual way. If the number and timing of technological innovations are unknown *a priori* then a grid search procedure similar to that conducted under the stationary model could be undertaken. That is, a specific number of technological innovations is assumed and a grid search procedure undertaken over the likelihood function to determine the most likely dates for that number of innovations to have occurred. This process is then repeated allowing for $i = 1, 2, \ldots, n$ innovations, and the final number of innovations is chosen based on results from sequential likelihood ratio tests. This allows the number and timing of technological innovations to be inferred from the data in much the same way as under the stationary model. Prior knowledge of the technology innovation and adoption process may again be used to rule out particular combinations of dates in order to reduce the dimensionality of this grid search procedure.

4. Application

The regime shift-diffusion model is illustrated by applying it to the growth of maize yields in Zimbabwe's large-scale farming sector. Data on the logarithm of maize yields in the large-scale farming sector of Zimbabwe between 1928 and 1995 are shown in figure 1.[2] Visual inspection indicates that yield growth appears to have gone through three main phases. The first phase, from 1928 through to the early 1950s, is characterised by zero growth, or perhaps a slow decline in trend yields. Then in the early 1950s there appears to have been a major shift to a high growth regime. This lasted until the mid-1970s, at which time the earlier zero growth or slow decline regime seems to have become re-established. The challenge is to develop a model

[2] Data are from Ministry of Agriculture in Zimbabwe. We thank Joseph Rusike for supplying us with them.

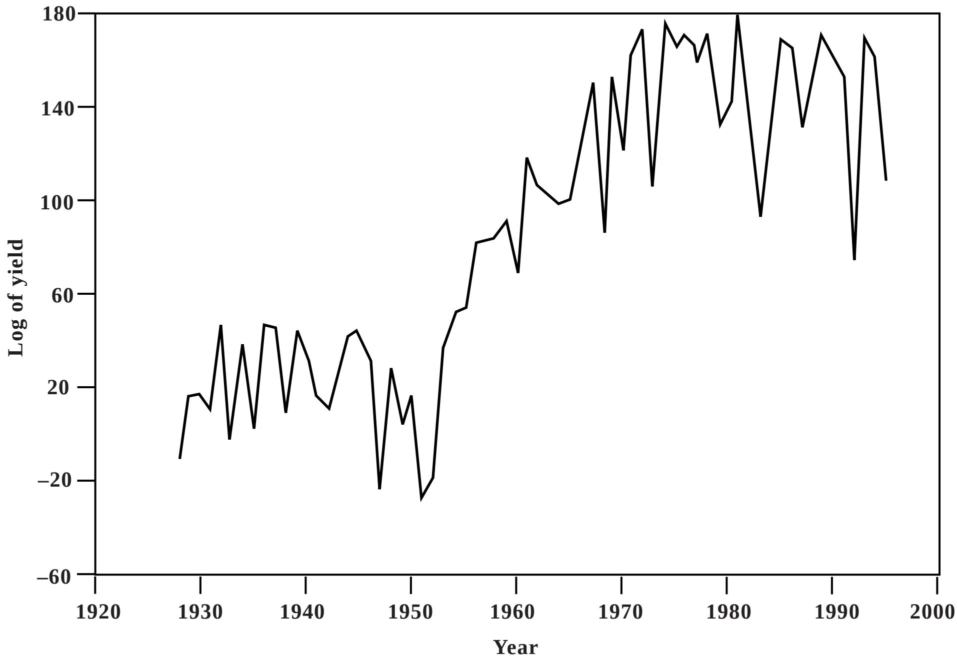

Figure 1 Commercial maize yields in Zimbabwe

which can explain these data as the outcome of a regime shift-diffusion process.

The increase in yields during the 1950s coincides with the release in 1949 of the first double hybrid, named SR1, bred in Zimbabwe for local conditions. Another important innovation was the release in 1960 of the single hybrid, SR52, which made Zimbabwe the first country in the world to use a single hybrid commercially (Tattersfield and Havazvidi 1994). SR52 continues to be grown on many of Zimbabwe's commercial farms more than 30 years after its initial release (Mashingaidze 1994). There was also a five-fold increase in fertiliser use between 1950 and 1965, along with an expansion of the land base used in maize production. These developments suggest at least one major regime shift in maize yield growth during the early 1950s, and perhaps a second shift occurring around 1960.

The first task in estimation is to determine whether yields should be modelled as stationary around a linear trend with regime shifts (equation (8)) or as difference stationary with a drift term that is subject to regime shifts (equation (9)). If the incorrect equation is used, then potentially serious errors in inference can occur (Stock and Watson 1988). Perron (1989), Perron and Vogelsang (1992) and Banerjee, Lumsdaine and Stock (1992), have developed tests for the null hypothesis of difference stationarity, with a drift term that is subject to a single regime shift, against the alternative of stationarity around a linear trend with a break point. However, these tests cannot be used here for two reasons. First, these tests require only a single regime shift and our model allows for multiple regime shifts. Second, these tests do not allow for a diffusion path which is a critical feature of the model used here.

Because there are no formal hypothesis tests available for testing equation (9) against equation (8), we proceed by comparing the two equations informally. We begin by estimating the stationary equation (8) using maximum likelihood. If the nonstationary equation (9) actually generated these data then the residuals $\{\hat{v}_t\}_t^T = 1$ from estimation of the stationary model should be nonstationary. Thus, following Perron (1989) we then estimate models of the form:

$$\Delta\hat{v}_t = \rho\hat{v}_{t-1} + \sum_{j=1}^{k} \phi_j \Delta\hat{v}_{t-j} + w_t \tag{10}$$

where k is chosen to eliminate autocorrelation, and examine the t-statistic on the null hypothesis of nonstationarity, $\rho = 0$, versus the stationary alternative $\rho < 0$. We would like to conduct a formal hypothesis test but, unfortunately, the distribution of the resulting test statistic depends on the regime shift and diffusion path parameters and is currently unknown. Thus, while this approach follows the spirit of standard Dickey-Fuller tests for nonstationarity, the t-value on ρ can only be viewed as suggestive and must be interpreted with care.

Another informal approach to examining the stationarity versus nonstationarity hypothesis is to take the same residuals $\{\hat{v}_t\}_t^T = 1$ from the estimated stationary model and use them to calculate the Kwiatkowski, Phillips, Schmidt and Shin (1992) LM statistic for testing the null of stationarity against the alternative of nonstationarity. This test is useful because it has been found that results from tests for nonstationarity can be quite sensitive to which hypothesis (stationarity or nonstationarity) is used as the null. Once again, however, the distribution of this statistic when regime shifts and diffusion paths are included is currently unknown. Thus, the results must be viewed as suggestive rather than as a formal hypothesis test.

The final informal approach is to take the residuals $\{\hat{v}_t\}_t^T = 1$ and simply examine their autocorrelation function. If the autocorrelation function is typical of a stationary, as opposed to a nonstationary series, then this would be further informal evidence in favour of the stationary model.

Table 1 Statistics for choosing between the stationary and nonstationary versions of the regime shift-diffusion model

Statistic	Single regime shift model	Two regime shifts model
ρ-value	− 1.095	− 1.134
t-statistic	− 8.952	− 9.336
1% critical value	− 5.58	− 5.58
KPSS statistic	0.049	0.037
10% critical value	0.119	0.119
Autocorrelations		
Lag 1	− 0.093	− 0.132
Lag 2	− 0.115	− 0.149
Lag 3	0.053	0.031
Lag 4	0.079	0.071
Lag 5	0.179	0.182
Std. Error	0.130	0.12

Note: ρ-value is the estimated value of ρ from equation (10), using zero lagged differences, and t-value is its associated t-statistic. The 1 per cent critical value provided is from Perron and Vogelsang (1992) and should not be interpreted as a formal critical value for t-value under multiple regime shifts and diffusion. KPSS-value is the Kwiatkowski *et al.* (1992) statistic computed from residuals from the stationary regime shift-diffusion model. The 10 per cent critical value is from Kwiatkowski *et al.* (1992) and should not be interpreted as a formal critical value for KPSS-value under multiple regime shifts and diffusion.

Results from implementing these procedures are shown in table 1. The procedures were applied to both a single regime shift model, with the shift occurring in 1950, and a two regime shift model with shifts in 1950 and 1961. In both cases the results are very similar. The estimated ρ value is much closer to minus one than to zero and the t-statistic for the null that $\rho = 0$ is much larger than the 1 per cent critical values cited by Perron and Vogelsang (1992), and Banerjee, Lumsdaine and Stock (1992), for the case of a single regime shift with no diffusion path. While this does not constitute a formal hypothesis test, the result is consistent with the view that the stationary model is appropriate. The calculated Kwiatkowski *et al.* (1992) statistics are much lower than even the 10 per cent critical values provided in Kwiatkowski *et al.* (1992) for testing the null of stationarity. Again, this does not constitute a formal hypothesis test but is consistent with stationarity. Finally, the estimated autocorrelations of the residuals from the stationary model are much more consistent with a white noise representation than a unit root process. None of the autocorrelations appear to be significantly different from zero. These results support the view that the regime shift-diffusion model can be specified and estimated in the stationary form (8), rather than the first difference form (9), and the remainder of the analysis proceeds under the stationary specification.

The stationary model was estimated initially assuming a single regime shift, no autocorrelation in ε_t, and ε_t normally distributed. The likelihood function is maximised when the regime shift occurs at 1950 and estimation results are provided in the first column of table 2. The lag length for the numerator polynomial of the diffusion path was set at $m = 5$ because this gave the best fit to the data. Results are not sensitive to the value used for m.

Because the data are in logarithms (multiplied by 100), the estimate of $\hat{\beta}_1 = 171$ per cent from table 2 can be interpreted as the total long-run percentage contribution of the 1950 regime shift to maize yield growth. Furthermore, the estimate of $\hat{\mu} = -0.83$ per cent suggests that, in the

Table 2 Estimation results for the regime shift-diffusion models

Parameter	Shift regime shift model	Two regime shifts model
τ_0	29.72 (8.81)	29.02 (8.19)
μ	– 0.83 (0.54)	– 0.80 (0.49)
β_1	171.31 (27.68)	108.72 (27.55)
β_2	—	55.08 (20.00)
δ	0.91 (0.16)	0.81 (0.07)
σ^2_ε	576.85 (98.94)	554.46 (95.09)
Log Likelihood	– 312.65	– 311.30
Q-statistics		
– Lag 1	0.600 (0.439)	1.202 (0.273)
– Lag 2	1.491 (0.475)	2.714 (0.257)
– Lag 5	4.160 (0.527)	5.250 (0.386)

Note: Numbers in parenthesis under the coefficients are asymptotic standard errors while numbers in parentheses under Q-statistics are p-values for the null hypothesis of no autocorrelation in the residuals from the model.

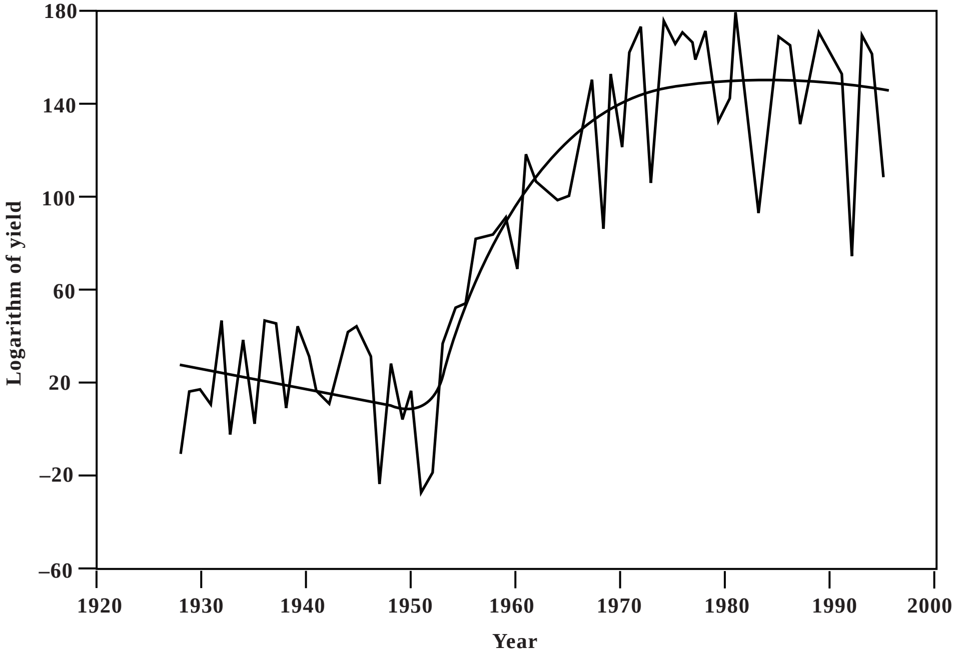

Figure 2 Trend yield path under a single regime shift

absence of new technological innovations, there is a constant 'depreciation rate' in maize yield growth of slightly less from 1 per cent per year. As stated earlier, this could be due to decreased resistance to pests and diseases, increased use of marginal lands, etc. However, this depreciation rate is not statistically different from zero at standard significance levels, and so we can conclude that there is no growth (or decline) in trend yield in the absence of regime shifts.

The estimated trend yield path under a single regime shift is shown in figure 2. The constant depreciation rate prior to 1950 is clearly visible, as is the 1950 regime shift. Trend yield increases slowly at first but then more rapidly. By the 1980s the period of rapid trend growth appears to have subsided. The diffusion path itself is isolated and shown in figure 3. The estimate of $\hat{\delta} = 0.91$ generates a very long and flat diffusion path, which suggests it takes almost 20 years for 80 per cent of the total effect of a regime shift to be incorporated into trend yields.

It is interesting that the estimated date of 1950 for when the single regime shift occurred corresponds with the initial introduction of hybrid seed into the large-scale maize sector of Zimbabwe. Indeed, the single regime shift in this model might be interpreted as the impact of a technological package which includes improved hybrid seed varieties,

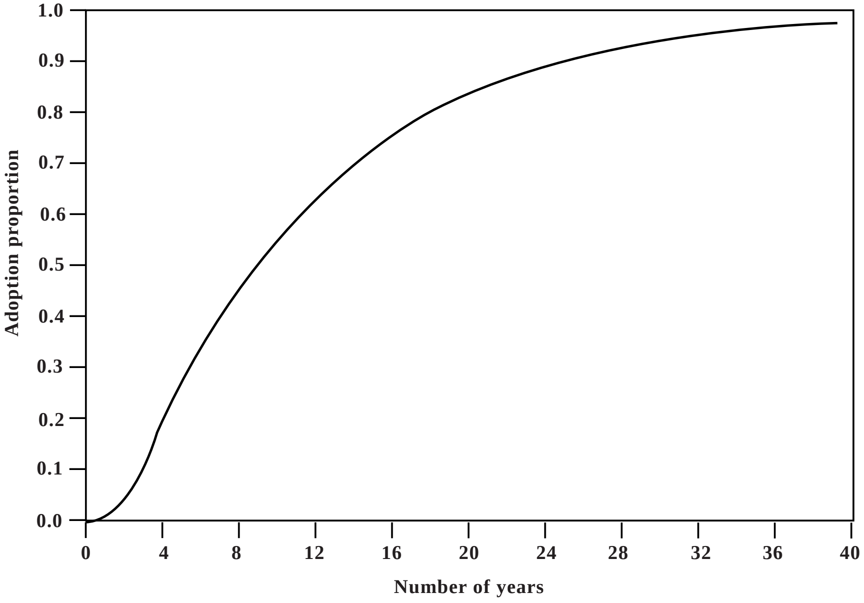

Figure 3 Diffusion path under a single regime shift

expanded use of commercial fertiliser, improved management practices, etc. which began around 1950.

Next the model was estimated allowing for two regime shifts, continuing to assume normally distributed and serially uncorrelated ε_t. A grid search was implemented allowing the first shift to occur between 1945 and 1955 and the second between 1957 and 1965. The likelihood function was maximised for an initial shift in 1950 and a second in 1963. However, all results were virtually identical irrespective of whether the second shift occurs in 1961, 1962, or 1963. Hence, we report results for 1961 because this is the year immediately following the release of a major new hybrid, SR52. As before, we estimated the models assuming $m = 5$ and results are not sensitive to this choice.

Results for the model with two regime shifts are given in the second column of table 2. The estimated depreciation rate remains at slightly under 1 per cent ($\hat{\mu} = -0.8$) but, again, this rate is not statistically different from zero at conventional significance levels. With two regime shifts the estimated total long-run contribution of the 1950 regime shift falls to $\hat{\beta}_1 = 109$ per cent as opposed to 171 per cent in the single regime shift model. However, the second regime shift in 1961 contributes an additional $\hat{\beta}_2 = 55$ per cent to trend yield growth, providing a total contribution of 164 per cent from both regime shifts.

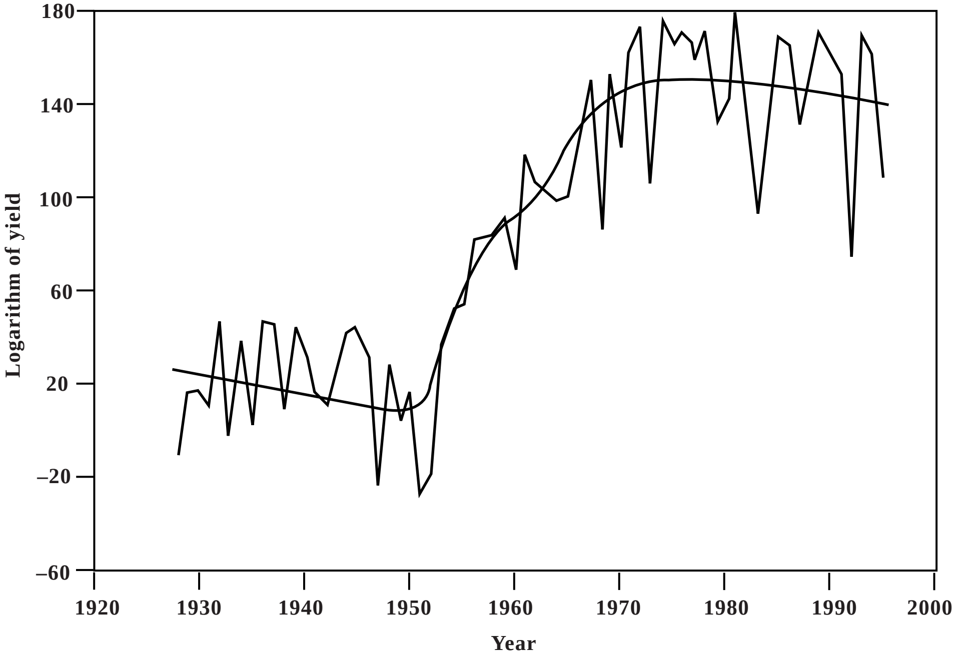

Figure 4 Trend yield path under two regime shifts

The estimated trend yield path for the two regime shift model is shown in figure 4 with the corresponding diffusion path in figure 5. The two innovations in 1950 and 1961, along with their associated diffusion paths, are clearly visible. Comparing figures 5 and 3 we see that the diffusion path under two regime shifts is much shorter and steeper than under the single regime shift, with 80 per cent of the effect now coming after 10 years, as opposed to 20 years in the single regime shift model.

The single regime shift model is nested in the two regime shift model and so a test of $\beta_2 = 0$ allows the models to be compared. An asymptotic t-test on $\beta_2 = 0$ generates a p-value of 0.003 while the likelihood ratio statistic for testing the same hypothesis is 2.7 with a p-value of 0.10. Clearly, the Wald and likelihood ratio tests give conflicting results in this application. However, given results of the t-test, the additional flexibility provided by the two regime shift model, and the fact that the length of the diffusion path in the two regime shift model is more consistent with prior information on the speed of technology diffusion in agriculture, we conclude that the model with two regime shifts is the preferred model. Models with three regime shifts were also investigated but these led to little additional explanatory power over the two regime shift model. As a final check on model specification Q, tests for first, second, and fifth degree autocorrelation in the error terms were

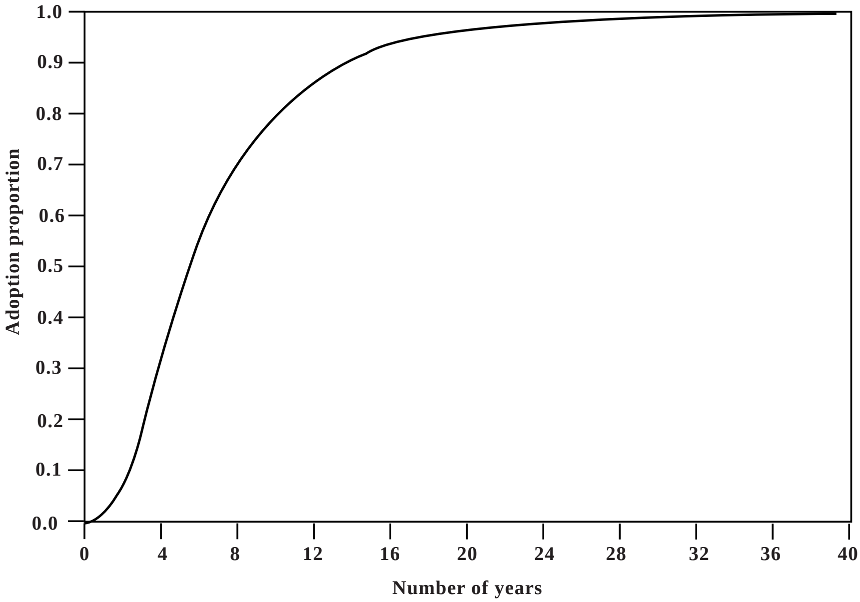

Figure 5 Diffusion path under two regime shifts

conducted. The results given in table 2 indicate that the null hypothesis of no autocorrelation is strongly supported in both models at all lags.

5. Concluding comments

This article introduces an alternative model of crop yield growth paths which allows for large infrequent innovations, or regime shifts, whose impacts follow a diffusion path. The shape of the diffusion path is specified *a priori* and used to identify the timing and effect of regime shifts. It is argued that the regime shift-diffusion model is more consistent with what we know about the actual process of technological innovation and diffusion in agriculture than are the more common polynomial or stochastic trend models of crop yield growth. Estimation of the regime shift-diffusion model only requires data on crop yields and allows the contribution of specific innovations in trend yield growth to be estimated, along with an estimate of the length of the corresponding diffusion path.

In an application to maize yields in Zimbabwe's large-scale farming sector the regime shift-diffusion model provided a good fit to the data. Results suggest that technological packages associated with the introduction of hybrid seed varieties have provided a major impetus to trend yield growth. Results also suggest that the diffusion path is quite long with at least 10 years required to absorb 80 per cent of the total contribution of a regime shift in crop yield growth, and 20 years required to absorb 95 per cent. It is also interesting to note that the results suggest that the major effect of technological innovations associated with the introduction of existing hybrid seeds has already been felt. Thus, without major new technological innovations, trend yield growth for large-scale maize in Zimbabwe is predicted to be entering a period of stagnation or slow decline.

Variation in the length and shape of technology diffusion paths can be interpreted as the lag between generation of new technology and its widespread adoption by farmers. Increases in yield can therefore be achieved either by development of new technologies and/or speeding up the rate of diffusion. Future research will focus on endogenising the diffusion path by identifying the contribution of underlying causal factors to the length and shape of the estimated diffusion paths.

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