Are Technology Shocks Nonlinear?

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Abstract

This paper examines the behavior of postwar real U.S. GNP, the inputs to an aggregate production function, and the associated Solow residuals for the presence of nonlinearities in their generating mechanisms. To test for nonlinearity, we implement three di®erent statistical tests: the McLeod-Li test based on the correlogram of the squared data, the BDS test based on the correlation integral, and the Hinich bicovariance test based on the third-order moments of the data.

We ¯nd substantial evidence that the generating mechanism of real GNP growth is nonlinear, but no evidence for nonlinearity in the Solow residual generated under alternative assumptions. We further ¯nd that the generating mechanism of the labor input series (expressed as hours worked) is nonlinear whereas that of the capital services input (expressed several ways) appears to be linear. We conclude that the source of the nonlinearity in real output is in the labor markets rather than in exogenous technology shocks. Finally, we examine the behavior of simulated factor input series from an asymmetric adjustment model to determine whether asymmetric adjustment costs are the source of the observed nonlinearities in the labor input.

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1 Introduction

A recent strand of the macroeconomics literature seeks to explain the behavior of key economic series in terms of nonlinear time series models. Notable among these analyses is Neftçi (1984), who models asymmetries in the cyclical behavior of the U.S. unemployment rate using a discrete Markov process. Other examples include Stock (1987) and Hamilton (1989), who propose nonlinear statistical models to describe the behavior of such series as output, unemployment, etc., while Hinich and Patterson (1985), Brock and Sayers (1988), and Ashley and Patterson (1989) test for nonlinearity in these series directly. Since a number of papers have found that the generating mechanism for real output is nonlinear and nonlinear in an asymmetric way - e.g., Blatt (1978), Neftçi (1984), Hamilton (1989), Ashley and Patterson (1989), and Potter (1995), and our own results reported below - it is of interest to determine the source of this nonlinearity.

In a related literature, a number of papers have shown the existence of an asymmetric response of factor demands to exogenous shocks across the business cycle. These results have been obtained using both aggregate and firm level data for a variety of countries. Notable among these contributions are the papers by Pfann and Palm (1993), and Palm and Pfann (1997), who use manufacturing data for the Netherlands, de la Croix, Palm, and Pfann (1996), who use aggregate and sectoral data for Belgium, France, and the Netherlands, and Pfann (1996), who uses manufacturing data for the U.K. and Netherlands. Hamermesh and Pfann (1996) examine the costs of adjusting the level of employment and the costs of hiring and firing using turnover data for U.S. manufacturing.

There are also a number of papers that have considered nonconvex and asymmetric adjustment cost models using firm-level data, including Pfann and Verspagen (1989), Jarambillo, Schiantarelli, and Semberelli (1993), Schiantarelli and Sembenelli (1993), and Bresson, Kramarz, and Sevestre (1993). A comprehensive review of this literature is provided by Hamermesh and Pfann (1996).

In this paper, we model the behavior of real output in terms of an aggregate production function and test for nonlinear serial dependence in the generating mechanisms for

- real output growth,
- its observable determinants (measures of the labor and capital inputs),
- an exogenous technology shock quantified by the Solow residual implied by this specification.

We also examine the behavior of simulated factor demand functions from a model with asymmetric adjustment costs to determine whether the asymmetric response of factor inputs to exogenous shocks across the business cycle can be used to account for nonlinearities in the generating mechanisms for real output and the factor inputs.

Following Solow's (1957) approach, technology shocks can be measured as the difference between the growth rate of output and the share-weighted growth rates of inputs. We review the conventional Solow residual approach in Section 2.1. However, this approach has been criticized on a number of grounds. If, for example, there is cyclical variation in factor utilization rates, then the conventional Solow residual inappropriately includes a component due to unobserved variation in capital and/or labor utilization rates.[1] Likewise, if there are increasing returns to scale in production or if firms have substantial market power due to imperfect competition, as argued by Hall (1988, 1990), then endogenous increases in efficiency due to scale effects or nonlinearity in the generating mechanism for the markup of price over marginal cost might spuriously cause the generating mechanism of the conventional Solow residual to appear to be nonlinear. In Section 2.2, we derive alternative measures of the Solow residual that account for such features.

What is meant by the term "nonlinear generating process" used above? Consider the closed and bounded metric space, S, of strictly stationary random processes with integer time indices, zero mean values, and finite higher moments. Let H denote an operator (called a filter) on this space; the range of the operator is a subset of the space S. If $\{\epsilon_t\}$ denotes an input process, then the output of the filter is denoted $x_t = H(\epsilon_t)$ at integer time, t. In the linear case, H is a linear, time-invariant, stable filter, and x_t can be written as a convolution of $\{\epsilon_t\}$ and an aboslutely summable sequence $\{h_t\}$, called the filter's impulse response:

$$x_t = \sum_{n=-\infty}^{\infty} h(n)\epsilon_{t-n}. \tag{1.1}$$

Next suppose that the filter represents a stable, time-invariant nonlinear operation on the input process. Just as the output of a linear filter is represented by its impulse response convolved with the input series, the output of a nonlinear filter that can be expressed as a convergent Volterra

[1] This is stressed by Abbot, Griliches, and Hausman (1988) and Basu (1996).

series expansion is completely represented by the multi-order convolution:

$$x_t = h_0 + \sum_{n=-\infty}^{\infty} h_1(n)\epsilon_{t-n} + \sum_{m=-\infty}^{\infty}\sum_{n=-\infty}^{\infty} h_2(m,n)\epsilon_{t-n}\epsilon_{t-m-n}$$

$$+ \sum_{k=-\infty}^{\infty}\sum_{m=-\infty}^{\infty}\sum_{n=-\infty}^{\infty} h_3(k,m,n)\epsilon_{t-n}\epsilon_{t-m-n}\epsilon_{t-k-m-n} + \cdots, \tag{1.2}$$

where the functions $h_i(n, m, k, \ldots)$ are called the Volterra kernels of the filter. (See Sanberg 1992.) The Volterra representation of a process is not always invertible. And not all nonlinear processes can be expressed as a Volterra series. However, all of the nonlinear processes that are of interest to economists can so be represented.

A nonlinear filter can be viewed as a device wherein the input to the system alters the filter's input response weights; i.e., the h(n) values in (1.1) change in response to the input process, $\{\epsilon_t\}$. That is, for each t and for each non-negative n, the n'th impulse response weight, h(n), is not constant but is instead a function of $\epsilon_{t-n}, \epsilon_{t-n-1}, \epsilon_{t-n-2}$, etc.

The most familiar examples of nonlinear processes in the economics literature are the ARCH and GARCH models of Engle (1982) and Bollerslev (1986). These models have proven useful in modelling the volatility of various financial time series, such as stock returns. ARCH and GARCH models belong to that class of stochastic processes called "martingale differences," models whose variates are serially dependent but nevertheless unforecastable.

As macroeconomists, we are typically most interested in those nonlinear models which are not martingale differences. If a member of the non-martingale class of nonlinear processes can be regarded as a good approximation for the dynamics of key macroeconomics time series, then the linear (or log-linear) forecasting/decision rules typically used in modelling expectations formation in macroeconomic models may be seriously flawed.

An example from Hinich and Patterson (1992) will help to make this point clear. Consider the following AR(1) model:

$$y_t = a y_{t-1} + u_t; \quad (|a| < 1); \tag{1.3}$$

where u_t is a stationary white noise series — i.e., u_t is not serially correlated. The conditional expectation of y_t is:

$$E\{y_t | y_{t-1}, y_{t-2}, \cdots\} = a y_{t-1}; \tag{1.4}$$

if and only if

$$E\{u_t | u_{t-1}, u_{t-2}, \cdots\} = 0; \tag{1.5}$$

which is to say, if and only if u_t is a martingale difference. Suppose, however, that the error sequence u_t is generated by the quadratic nonlinear process:

$$u_t = \epsilon_t + \sum_{m=1}^{\infty} a(m) \epsilon_{t-1} \epsilon_{t-m-1}; \tag{1.6}$$

where the ϵ_t are independently and identically distributed random variables and

$$A(z) = \sum_{m=1}^{\infty} a(m) z^m \tag{1.7}$$

has no zeroes inside the unit circle in the complex plane. This error sequence $\{u_t\}$ is not a martingale difference, so the conditional expectation of y_t is not ay_{t-1}, but rather:

$$E\{y_t | y_{t-1}, y_{t-2}, \cdots\} = ay_{t-1} + \sum_{m=1}^{\infty} a(m)\epsilon_{t-1}\epsilon_{t-m-1}, \tag{1.8}$$

where $\epsilon_{t-1}, \epsilon_{t-2}$ are observable at time t under the restrictions imposed on A(z). It is important to note that the error sequence given by (1.6) is serially uncorrelated (white) noise; its serial dependence will not be detected by the usual diagnostic tests.

This distinction between linear and nonlinear models is also potentially quite consequential for another reason: statistical inferences based on a structural model for y_t which is mistakenly specified to be linear can be seriously flawed. For example, innovations like u_t in equation (1.3) are ordinarily assumed to be at least asymptotically independent, so where u_t is actually serially dependent, as in equation (1.6), the usual statistical machinery is invalid.

Below, we test for nonlinearity in the generating mechanisms of U.S. real output, the inputs to an aggregate production function, and several estimates of the Solow residual. Three statistical tests are used:[2]

1. McLeod-Li test [McLeod and Li (1983)]

2. BDS test [Brock, Dechert, and Scheinkman (1996)]

3. Hinich bicovariance test [Hinich (1995), Hinich and Patterson (1995)]

[2] MS-DOS software implementing these tests is available from the authors as part of a "nonlinearity toolkit."

The McLeod-Li test is based on the sample correlogram of the square of the data. This test is examining selected fourth moments of the data; in essence, it is testing for conditional heteroscedasticity (ARCH) e®ects. The BDS test is based on a nonparametric measure of association between a time series and its recent past. Originally proposed as a test for deterministic chaos in economic time series, the BDS test is now typically applied to prewhitened data as a test for serial independence. The Hinich bicovariance test systematically examines third moments of the series; it is a time-domain analogue of the Hinich bispectral test. The Hinich bispectral test and the kinds of nonlinear generating mechanisms most amenable to detection by third-moment techniques are described in Hinich (1982), Hinich and Patterson (1985), Ashley, Patterson, and Hinich (1986), and Ashley and Patterson (1989).[3] The bicovariance test is used here in view of the small sample sizes available. Since all of these tests are valid only in large samples { very large samples in the case of the BDS test { the results presented below are all based on bootstrapped simulations.

These tests are described in more detail in Section 3; the results of applying them to test for nonlinearity in the generating mechanisms for real output, the input factor series (labor and capital services), and alternative measures of productivity or Solow residuals are presented in Section 4. There we are able to conclude that the source of the widely-observed nonlinearities in the generating mechanism for real output is most likely in the labor markets rather than in exogenous technology

[3] Third-moment techniques are sensitive to forms of nonlinearity that yield asymmetric time series; testing for asymmetry per se { as in Mittnik and Niu (1994), Ramsey and Rothman (1996), and Verbrugge (1996) { is beyond the scope of the present paper, however.

shocks. In Section 5, we use simulated series on labor, capital, and output based on the decision rules for a ¯rm with a Cobb-douglas production technology and asymmetric costs of adjustment to determine if the nonlinearity in the generating mechanism for the labor input can be attributed to the asymmetric response of labor demand to exogenous shocks.

2 A Framework

The procyclical behavior of measured productivity is one of the key issues in the current macroeconomics literature. According to proponents of the real business cycle approach (Prescott 1986) the observed procyclical movements in productivity are a response to exogenous technology shocks. In a series of papers, Hall (1988, 1990) has argued that the procyclicality of productivity can be attributed to imperfect competition and to internal increasing returns to scale in production. In this case, productivity can be procyclical even in the absence of positive technology shocks: a demand shock that stimulates output can be associated with increases in productivity by leading to endogenous increases in e±ciency. Labor hoarding or variable labor utilization rates have been given as another reason for the procyclical behavior of productivity. Rotemberg and Summers (1990) present a model with in°exible prices and labor hoarding which generates the procyclical movements in productivity observed in the data.

In this section, we ¯rst describe the conventional Solow residual framework, which allows us to treat the residual from an aggregate production function as an observable measure of technology shocks. Next we describe various extensions of the basic framework that attempt to account for some of the alternative factors that have been used to account for the cyclical behavior of productivity. Finally, we discuss how the tests implemented in this paper can be used to di®erentiate among the alternative models of cyclical °uctuations.

2.1 The Conventional Solow Residual Framework

Solow (1957) showed that if there are constant returns to scale, all factors are fully variable, and there is perfect competition in the product and factor markets, then the di®erence between the rate of growth of output and the share-weighted growth rates of inputs provides an observable measure of exogenous technological change. To describe his approach, consider a production function for aggregate output y_t as a function of capital services S_t, total hours worked L_t, and a random technology shock z_t as:

$$y_t = z_t F(S_t, L_t). \tag{2.1}$$

We initially assume that capital services are proportional to the stock of capital K_t:

$$S_t = \theta K_t. \tag{2.2}$$

Letting p_t denote the product price and w_t the wage rate, the assumptions that there are constant returns to scale in production and perfect competition in product markets imply that the growth rate of real output can be expressed:

$$\Delta \ln(y_t) = \alpha_t \Delta \ln(L_t) + (1 - \alpha_t) \Delta \ln(K_t) + \Delta \ln(z_t), \tag{2.3}$$

where α_t is the factor share earned by labor (the ratio of compensation $w_t L_t$ to total revenue $p_t y_t$) and where we have substituted for S_t using (2.2). Using (2.3), the Solow residual can be expressed as the difference between the growth rate of real output and the share-weighted growth rates of the inputs:

$$\Delta \ln(z_t^1) = \Delta \ln(y_t) - \alpha_t \Delta \ln(L_t) - (1 - \alpha_t) \Delta \ln(K_t). \tag{2.4}$$

The variable z_t is indexed by '1' to denote the Solow residual for our benchmark model.

2.2 Extensions to the Conventional Framework

The first alternative to the benchmark model relaxes the assumption that capital services are proportional to the stock of capital. In his original paper, Solow (1957) allowed for the possibility that capital utilization rates could vary across the business cycle by measuring capital services as the product of the physical capital stock and the employment rate. Other approaches to adjusting for variable capital utilization rates include using measures of electricity usage (Jorgenson and Griliches 1967), the Federal Reserve Board capacity utilization series (Tatom 1980), and shift data (Shapiro 1986 and Mayshar and Solon 1993). Following the recent practice in Burnside, Eichenbaum, and Rebelo (1995a,b), we assume that aggregate electricity usage, E_t, is proportional to capital services:[4]

$$E_t = \phi S_t. \tag{2.5}$$

Using the relationship (2.5) yields an alternative expression for the Solow residual as:

$$\Delta \ln(z_t^2) = \Delta \ln(y_t) - \alpha_t \Delta \ln(L_t) - (1 - \alpha_t) \Delta \ln(E_t). \tag{2.6}$$

A second criticism of the conventional Solow residual framework is that it does not account for variation in unobserved work effort across the business cycle. To show this, suppose total hours worked depends on the number of workers employed times their effective work effort.[5] Letting N_t denote the number of workers who are employed and W_t the level of effort expended by an individual, output is assumed to be produced according to the Cobb-Douglas production function:

$$y_t = z_t K_t^{1-\alpha} [f N_t W_t]^{\alpha}; \tag{2.7}$$

where f is the (fixed) shift length, so that fW_t denotes total effective work effort and $L_t = fN_t$. Proceeding as before, the Solow residual is:

$$\Delta \ln(z_t^3) = \Delta \ln(y_t) - \alpha [\Delta \ln(N_t) + \ln(W_t)] - (1 - \alpha) \Delta \ln(K_t). \tag{2.8}$$

This expression shows that unmeasured variation in work effort enters as an additional determinant of observed measures of productivity. The conventional Solow residual is related to $\Delta \ln(z_t^3)$ as

[4] Our definition of the electricity usage series differs from Burnside et al in that we use the monthly index of electric utility sales to commercial and other users whereas these authors use a monthly index of total electrical power usage in the industrial sector (manufacturing plus mining plus utility industries).

[5] Our discussion is based on Burnside, Eichenbaum, and Rebelo (1993).

follows:

$$\Delta \ln(z_t^1) = \Delta \ln(z_t^3) + \alpha \Delta \ln(W_t). \tag{2.9}$$

If z_t^3 is taken to be identical to the "true" technology shock z_t, then the expression in (2.9) implies that the conventional Solow residual can confound movements in technology with movements in unobserved work effort across the cycle, which itself responds to exogenous "demand shocks," such as government consumption shocks. Following the approach in Abbott, Griliches, and Hausman (1988) or Caballero and Lyons (1992), we allow for the effects of variable labor utilization by testing the behavior of average hours worked per worker for potential nonlinearities.

A third criticism stems from the fact that the conventional Solow residual confounds endogenous changes in efficiency due to the presence of increasing returns in production with exogenous changes in productivity. Likewise, it does not take into account the existence of market power by firms. To allow for these features, we use the "cost-based" Solow residual proposed by Hall (1988, 1990). Letting r_t denote the service price of capital and defining α_t^c as the share of labor in total costs, $\alpha_t^c \equiv w_t L_t/(w_t L_t + r_t K_t)$, the cost-based Solow residual can be expressed as:

$$\Delta \ln(z_t^4) = \Delta \ln(y_t) - \gamma \left[\alpha_t^c \Delta \ln(L_t) + (1 - \alpha_t^c) \Delta \ln(K_t)\right], \tag{2.10}$$

where γ denote the returns to scale of the aggregate production function. To see the effect of increasing returns on the measurement of productivity, consider the difference:

$$\Delta \ln(z_t^1) = \Delta \ln(z_t^4) + (\gamma - 1)\left[\alpha_t^c \Delta \ln(L_t) + (1 - \alpha_t^c) \Delta \ln(K_t)\right]. \tag{2.11}$$

This expression shows that the conventional Solow residual confounds exogenous increases in technology with endogenous increases in output due to scale effects.

The effect of imperfect competition on observed measures of productivity can also be demonstrated using (2.10). Assuming that the product price p_t contains a markup μ over marginal cost, it is straightforward to show that the relationship between the revenue and cost shares is $\gamma c_{Jt} = \mu s_{Jt}$, $J = K; L$. Substituting this relation in (2.10) implies that:

$$\Delta \ln(z_t^1) = \Delta \ln(z_t^4) + (\mu - 1)\left[\alpha_t \Delta \ln(L_t) + (1 - \alpha_t) \Delta \ln(K_t)\right]: \tag{2.12}$$

Under imperfect competition, price exceeds marginal cost. Hence, the conventional Solow residual misinterprets increases in the value of output relative to increases in the value of inputs as improvements in technology.

2.3 Implications

When implementing tests of nonlinearity in the generating mechanism for real output, the inputs of labor and capital, and an observable measure of technology shocks, one can ask (1) what are the implications of a linear versus nonlinear generating mechanism for a given variable, and (2) what classes of dynamic macroeconomic models can generate the types of nonlinearities that the tests in this paper can detect?

In terms of the first question, if technology shocks have a nonlinear generating mechanism of the type discussed in the Introduction, then linear time series methods (as in Cochrane (1994)) are not useful in quantifying the relative importance of alternative types of shocks in generating cyclical °uctuations. The reason is that nonlinearities in the generating mechanism for the exogenous shocks will translate into nonlinear behavior in the observed series; consequently, linear models for the observed series will be mis-speci¯ed and conclusions based on them unreliable. If the source of the nonlinearity in the generating mechanism for an endogenous variable such as real output is found to lie in the propagation mechanism for the exogenous shocks, then explaining the behavior of cyclical °uctuations requires that we identify the mechanism generating the nonlinearity. Put di®erently, the dynamic behavior of an economy that contains features leading to nonlinearities in the behavior of the endogenous series will be distorted when analyzed using the VAR approach proposed by Sims (1980) or the simple linear (or log-linear) decision rules described, for example, by Kydland and Prescott (1982).

In response to the second question, consider the simple model of labor hoarding described by Hall (1990). The technology is constant returns to scale, with y units of output produced for L units of the labor input, i. e. $y = L$. However, the response of employment is di®erent in recessions versus booms. Speci¯cally, in recessions, if output goes down by one unit, employment decreases by only Á units (Á < 1) because ¯rms ¯nd it costly to ¯re workers in recessions and re-hire them in booms. This version of the labor hoarding model gives rise to a simple threshold model in which changes in employment are described by a di®erent model depending on whether changes in output are positive or negative, that is,

$$\Delta L = \begin{cases} \Delta y & \text{if } \Delta y > 0 \\ \phi \Delta y & \text{if } \Delta y < 0. \end{cases} \tag{2.13}$$

Monte Carlo simulations in Ashley and Patterson (1989) show that the Hinich bispectral test has considerable power to detect univariate threshold AR models, the analogue of equation (2.13) in a setting with stochastic dynamics. This kind of asymmetric factor demand also arises in the asymmetric adjustment cost model considered in Section 5 below.

3 Testing for Nonlinearities

In this section, we provide a brief description of the statistical tests implemented below. These include a test for ARCH effects due to McLeod and Li (1983), the BDS test proposed by Brock, Dechert, and Scheinkman (1996), and the bicovariance test due to Hinich (1995) and Hinich and Patterson (1995). These tests all share the same premise: once any linear serial dependence is removed from the data via a prewhitening model, any remaining serial dependence must be due to a nonlinear generating mechanism. Thus, each of the three procedures is actually a test of serial independence applied to the (by construction) serially uncorrelated fitting errors of an AR(p) model for the sample data. This fitting error series, standardized to zero mean and unit variance, is denoted by $\{x_t\}$ below.

<u>The McLeod-Li Test</u>

This test for ARCH effects was proposed by McLeod and Li (1983) based on a suggestion in Granger and Andersen (1978). It looks at the autocorrelation function of the squares of the prewhitened data and tests whether $\mathrm{corr}(x_t^2, x_{t-k}^2)$ is non-zero for some k. The autocorrelation function for the squared residuals $\{x_t^2\}$ is estimated by:

$$\hat{r}_{xx}(k) = \sum_{t=k+1}^{T} (x_t^2 - \hat{\sigma}^2)(x_{t-k}^2 - \hat{\sigma}^2) \Big/ \sum_{t=1}^{T} (x_t^2 - \hat{\sigma}^2)^2, \tag{3.1}$$

where

$$\hat{\sigma}^2 = \sum_{t=1}^{T} x_t^2 / T.$$

Under the null hypothesis that $\{x_t\}$ is an i.i.d process (and assuming that $E\left(x_t^2\right)$ exists) McLeod and Li (1983) show that, for fixed M:

$$\sqrt{T}\hat{r}_{xx} \equiv (\hat{r}_{xx}(1), \ldots, \hat{r}_{xx}(M)) \tag{3.2}$$

is asymptotically a multivariate unit normal. Thus,

$$Q_{xx}^{*} = T(T+2) \sum_{i=1}^{M} \hat{r}_{xx}^2(i)/(T-i), \tag{3.3}$$

is asymptotically $\chi^2(M)$ under the null hypothesis of a linear generating mechanism for the data.

The BDS Test

The BDS test is a nonparametric test for serial independence based on the correlation integral of the scalar series, $\{x_t\}$. For embedding dimension m, let $\{x_t^m\}$ denote the sequence of m-histories generated by $\{x_t\}$:

$$x_t^m \equiv (x_t, \ldots, x_{t+m-1}).$$

Then the correlation integral $C_{m,T}(\epsilon)$ for a realization of $\{x_t\}$ of length T is given by:

$$C_{m,T}(\epsilon) = \sum_{t<s} I_\epsilon(x_t^m, x_s^m) \times [2/(T_m(T_m - 1))]; \tag{3.4}$$

where $T_m = T - (m - 1)$ and $I_\epsilon(x_t^m, x_s^m)$ is an indicator function which equals one if the sup norm $\|x_t^m - x_s^m\| < \epsilon$ and equals 0 otherwise. Brock, Dechert, and Scheinkman (1996) exploit the asymptotic normality of $C_{m,T}(\epsilon)$ under the null hypothesis that $\{x_t\}$ is an i.i.d. process to obtain a test statistic which asymptotically converges to a unit normal.

<u>The Hinich Bicovariance Test</u>

This test assumes that $\{x_t\}$ is a realization from a third-order stationary stochastic process and tests for serial independence using the sample bicovariances of the data. The (r, s) sample bicovariance is defined as:

$$C_{Z3}(r,s) = (T - s)^{-1} \sum_{t=1}^{T-s} x_t x_{t+r} x_{t+s} \quad \text{for } 0 \leq r \leq s. \tag{3.5}$$

Under the null hypothesis that $\{x_t\}$ is an i.i.d. process, Hinich and Patterson (1995) show that, for $\ell < T^{.5}$,

$$CH_3 = (T - s)^{.5} \sum_{s=2}^{\ell} \sum_{r=1}^{s-1} C_{Z3}^2(r,s); \tag{3.6}$$

is asymptotically distributed chi-square with $df = (\ell - 1)\ell/2$ degrees of freedom. Hinich and Patterson (1995) recommend using $\ell = T^{.4}$ since they find that the power of the test declines for smaller values of ℓ.

4 Results

Table 2 reports the results of the Hinich bicovariance test and the McLeod-Li test for real output, capital, and two labor series; Table 3 reports analogous results using the BDS test. Each entry in Tables 2 and 3 is the marginal signi¯cance level at which the null hypothesis of a linear generating mechanism can be rejected, based on 1000 bootstrap replications.

Output is measured using real U.S. GNP; its growth rate is denoted LY below. Two alternative measures of total hours worked are used: the ¯rst measure is manhours employed per week for all workers in all industries; the second is total employee-hours in nonagricultural establishments. The growth rates in these two series are denoted LH1 and LH2 below; these lead to the construction of two di®erent Solow residual series, denoted SOL1 and SOL2 below, respectively. The quarterly capital stock series utilized below is constructed using computations similar to those in Christiano (1988) and Burnside, Eichenbaum, and Rebelo (1995a). Its growth rate (LC) is used in equation (2.4) but the nonlinearity tests are applied to LCDIF, the change in LC, since the time series behavior of LC itself (which is constructed as the cumulation of net investment) is dominated by a unit root. These acronyms and de¯nitions are summarized in Table 1; a more detailed description of our data sources and methodology can be found in the Appendix.

A time plot of the observable series is given in Figure 1 while the associated Solow residuals are plotted in Figure 2. As noted in Section 3, all three statistical tests are implemented on prewhitened data. Each series is prewhitened using an AR(p) model, with the order p chosen to minimize the Schwartz (SC) criterion.[6] Since the sample is not very large, we do not accept these choices mechanically: we routinely check the nonlinearity test results with alternative AR(p) order speci¯cations whenever the SC-based model estimates are not clearly satisfactory, so as to verify that the test results do not materially depend on the choice made.

In considering the results displayed in Tables 2 and 3, we note:

1. Both the BDS and the Hinich bicovariance tests con¯rm the results from the previous studies cited in Section 1: the null hypothesis of a linear generating mechanism for aggregate real output can be rejected at the 1-2% level of signi¯cance.

2. The null hypothesis of a linear generating mechanism cannot be rejected at the 5% level for either speci¯cation of the Solow residual using any of the tests.

3. The null hypothesis of a linear generating mechanism cannot be rejected at even the 35% level for the capital stock series using any of the tests.

4. The null hypothesis of a linear generating mechanism can be rejected at the 2-5% level for one of the hours worked series (LH1) and can be resoundingly rejected for the other, LH2.

Tables 4 and 5 summarize the results of the Hinich bicovariance and McLeod-Li tests (Table 4) and the BDS test (Table 5) for the electricity usage series LECTRIC (which proxies for capital services), for the average hours worked series LHAVG (which proxies for unobserved variation in work

[6] In contrast to alternative choices (e.g., AIC or FPE), the Schwartz criterion is known to be consistent for AR(p) order determination under the null hypothesis of a linear generating mechanism; see Judge, et al. (1985, p. 246).

e®ort), and for six alternative de¯nitions of the Solow residual { SOLE1 through SOLCE1 { that use di®erent measures of capital services and the labor input and allow for imperfect competition. Two alternative Solow residual series, denoted SOLE1 and SOLE2, respectively, were generated using equation (2.6) and the series LECTRIC,[7] depending on which of the two hours worked series (LH1 or LH2) is used. Equation (2.10) was used to generate four cost-based Solow residuals { denoted SOLC1, SOLC2, SOLCE1, and SOLCE2 { depending on which of the two hours worked series (LH1 or LH2) and which of the two capital stock series (LCDIF or LECTRIC) is used.[8] None of the results in Tables 4 and 5 would allow one to reject the null hypothesis of a linear generating mechanism for LECTRIC, LHAVG, and SOLE1 through SOLCE2 at the 5% level.[9]

These results using LECTRIC, SOLE1, SOLE2, SOLCE1, and SOLCE2 indicate that our conclusions are robust with respect to using electricity usage to proxy for variable capital utilization rates across the business cycle. Similarly, the result on LHAVG indicates that unmeasured variations in work e®ort across the business cycle are not a signi¯cant source of the observed nonlinearity

[7] The statistical behavior of this time series was notably a®ected by a pair of outliers in 1973:IV and 1974:I; consequently, these two observations were set equal to the sample mean.

[8] In these calculations, the parameter ° was set equal to one.

[9] The results for SOLC2 are based on observations up to 1987:4 because the series appears to exhibit nonstationarity over the full sample. Likewise, an outlier was eliminated from LHAVG for 1970:3. The bicovariance test indicates some evidence against linearity for the average hours worked per worker series; however, in view of the number of tests performed, we do not view our results on this series as a clear rejection of the linear generating mechanism hypothesis, even at the 5% level.

in real output. Finally, the results on SOLC1, SOLC2, SOLCE1, AND SOLCE2 indicate that our results are robust with respect to using the "cost-based" Solow residual framework proposed by Hall (1988, 1990) to account for the e®ects of increasing returns to production and/or imperfect competition. In summary, our result - that a linear generating mechanism for the Solow residual cannot be rejected - is robust with respect to all of the alternatives to the conventional Solow residual framework discussed in Section 2.2 above.

Most importantly { having ruled out nonlinearity in the capital markets and having ruled out nonlinearity in the generating mechanism of exogenous technical shocks across a variety of approaches to measuring such shocks { we do ¯nd strong evidence of a nonlinear generating mechanism for either measure of the labor input to the aggregate production function. Thus, we can conclude that the observed nonlinearity in the generating mechanism for aggregate real output is in fact arising from nonlinearities in the markets for labor.

As noted in the Introduction, an asymmetric response of employment across the business cycle has been documented for a number of di®erent data sets and for a variety of European countries as well as the U.S. Since such asymmetries are characteristic of many nonlinear generating mechanisms, our results are consistent with those obtained in that literature. In the next Section, we examine data simulated from the estimated decision rules for an asymmetric adjustment model of the type proposed by Pfann and Verspagen (1989), Pfann (1996), and Palm and Pfann (1997) using Dutch data, to see if a similar pattern of nonlinearity test results obtains.

5 Results Using Simulated Data from a Model With Asymmetric Adjustment Costs

In the results described above, we test U.S. data on the growth rates of output, capital, labor and the implied Solow residual. In this Section, we apply the nonlinearity tests to simulated output, capital, and labor data from an asymmetric adjustment cost model of the Dutch manufacturing sector due to Palm and Pfann (1997). Their model assumes linear productivity shocks, but this is consistent with our results for Solow residuals in the U.S. economy. The data simulated from their model allows us to determine whether the estimated Palm/Pfann model does or does not yield a pattern of nonlinearity results for output, capital, and labor similar to that which we found using U.S. data directly.[10]

The Palm/Pfann model derives factor demands from the real present value maximization problem of a firm that chooses the optimal quantities of labor and capital denoted L_t and K_t, respectively, taking as given the real price of investemnt q_t and real wage costs w_t. The firm's objective function is given by:

$$E_0 \left\{ \sum_{t=0}^{\infty} \beta^t (Y_t - VC_t - AAC_t) \right\} ; \tag{5.1}$$

where $\beta = 1/(1+r)$ is the constant discount rate, Y_t denotes output, VC_t denotes the variable costs of production, AAC_t the (asymmetric) adjustment costs, and E_0 is expectation conditional on information at date zero.

[10] Unfortunately, the original sample ($N = 72$) is too small to support a direct examination of the Dutch data.

Output is assumed to be produced according to the Cobb-Douglas production function:

$$Y_t = z_t K_t^{1-\alpha} L_t^{\alpha}; \quad 0 < \alpha < 1; \tag{5.2}$$

and variable costs are given by:

$$VC_t = q_t (K_t - (1-\delta)K_{t-1}) + w_t L_t. \tag{5.3}$$

The specification of adjustment costs follows Pfann and Verspagen (1989) and includes the linear-quadratic specification as a special case:

$$AAC_t = AAC(\Delta K_t) + AAC(\Delta L_t); \tag{5.4}$$

where $AAC(\Delta K_t) = \exp(\beta_K \Delta K_t) - 1 - \beta_K \Delta K_t + \frac{1}{2}\gamma_K(\Delta K_t)^2$, $AAC(\Delta L_t) = \exp(\beta_L \Delta L_t) - 1 - \beta_L \Delta L_t + \frac{1}{2}\gamma_L(\Delta L_t)^2$, Δ is the first-difference operator, γ_K and γ_L are constant parameters that measure the adjustment costs of net changes in capital and labor, and β_K and β_L are constant parameters that measure the marginal asymmetry between positive and negative net changes in factor inputs.

The optimal contingency plans for labor and capital satisfy a set of first-order conditions obtained by diffentiating the objective function in (5.1) with respect to L_t and K_t for $t = 0, 1, 2, \ldots$ Palm and Pfann (1997) estimate the parameters of the model based on the first-order optimality conditions using a generalized method of moments approach with data on the manufacturing sector for the Netherlands. As part of their analysis, these authors also solve for approximate decision rules for L_t and K_t as a function of the exogenous series using the parameterized expectations algorithm proposed by Der Haan and Marcet (1990).

Palm and Pfann's model is, in part, driven by an external bivariate real factor price process. They consider two such generating processes for real factor prices, one which is quadratic and another which is linear, yielding two sets of simulated output, capital, and employment data.

Our test results for these data are given in Tables 6 and 7, respectively. Both factor price simulations yield similar results for the capital and labor series: both labor series show little or no sign of a nonlinear generating process, whereas both capital series are highly nonlinear. (The output series is highly nonlinear in the simulations based on the linear factor price process and not signi¯cantly nonlinear in the simulations based on the nonlinear factor price process: apparently the °uctuations in output are largely driven by the capital °uctuations in the former instance and by employment °uctuations in the latter.) This is a di®erent pattern from what we observe in the U.S. data, as shown in Table 1: there the generating mechanism for capital appears linear whereas the generating mechanism for employment is nonlinear. Whether this discrepancy is due to di®erences in the two economies or to counterfactual restrictions in the Palm/Pfann model is, at this point, an open question. However, conditional on the assumption that the Palm/Pfann model is a reasonable representation of the Dutch economy, our results suggest that there are fundamental di®erences in the dynamic behavior of the Dutch and U.S. economies.

6 Conclusion

We have presented the results of several alternative tests for nonlinearity in the generating mechanisms of real GNP, the inputs to an aggregate production function, and the Solow residuals derived under several sets of assumptions about the measurement of inputs and the nature of competition in product markets. We ¯nd substantial evidence that the generating mechanism for real GNP exhibits nonlinear serial dependence, but no evidence at all for nonlinearity in the generating mechanism for the Solow residuals under any of the di®erent speci¯cations that we studied. In principle, this result for the Solow residuals could be due to insu±cient power in our tests due to the small size of the sample. However, the fact that we do detect nonlinearity in the generating mechanisms for real GNP growth and for the growth rate of total hours worked over the same sample period indicates that the power of the tests is not the problem: we are not detecting nonlinear serial dependence in the Solow residuals because there simply isn't much there to detect.

We intrepret this result as implying that it is the macroeconomy itself which is nonlinear { not the technology (or factor productivity) shocks that are impinging on, and in part, driving it. While we have not considered the behavior of other types of shocks such as demand shocks, our evidence with respect to the di®erent series suggests that nonlinear models for the behavior of aggregate output need to be considered rather than nonlinear models for the shocks themselves. And { since these results indicate that any statistically adequate macroeconomic model must be signi¯cantly nonlinear { the modelling of rational expectations formation must explicitly take this nonlinearity into account.

The generating mechanisms for the measures of the capital services input do not appear to be significantly nonlinear; in contrast, we find that the generating mechanism for total employment is significantly nonlinear. The combination of this result with our finding that the generating mechanism for the Solow residual is not significantly nonlinear implies that the nonlinearity in real output documented in this and previous studies can be largely attributed to the nonlinearity we and others (as listed in the Introduction) have shown for the generating mechanism for employment and hours worked. As one possible propagation mechanism generating the nonlinearity in the labor input series, we examine the behavior of simulated factor input demands from an asymmetric adjustment cost model estimated for the manufacturing sector in the Netherlands, and find that, contrary to our results using U.S. data, it is the capital input series that displays a nonlinear generating mechanism and not the labor input series. We leave for future work the further examination of alternative models that can potentially generate the patterns of nonlinearities that we have documented in this paper.

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Data

The data are quarterly observations for the aggregate economy. Real output is measured as gross national product in 1987 dollars from the National Income and Product Accounts (NIPA), Table 1.10. Total hours worked are measured in two di®erent ways: ¯rst, as manhours employed per week for all workers, all industries, derived from the Household Survey of the Bureau of Labor Statistics publication, The Employment Situation, and second, as total employee-hours for wage and salary workers in nonagricultural establishments. The corresponding CITIBASE codes are LHOURS and LPMHU, respectively. Multiplying the ¯rst variable LHOURS (manhours worked per week for all workers, all industries) by the number of weeks in a quarter yields the ¯rst measure of total hours worked, LH1. The second measure of total hours worked, LH2, is obtained by time aggregating the monthly series LPMHU. Average hours worked is calculated by dividing LPMHU by nonfarm employment, LPNAG. The series on electricity usage is de¯ned as the monthly index of electric utility sales to commercial and other users; its CITIBASE code is IPCOE. All quarterly series are derived as three month averages of the monthly series.

There is no published quarterly data on di®erent components of the aggregate capital stock. We obtained annual data from the Bureau of Economic Analysis capital stock tables described in the publication, Fixed Reproducible Tangible Wealth of the U.S., 1989. These data are for the period 1946-1993 and include annual measures of the gross and net stocks of private nonresidential structures and producers' durable equipment (which comprise the stock of ¯xed nonresidential private capital), residential capital, and government owned fixed capital consisting of equipment and structures in 1987 dollars. Our measure of the aggregate net capital stock is obtained as the sum of the different components of the gross capital stocks, interpolated to a quarterly basis using the method in Fernandez (1981), and corrected for depreciation. We used quarterly data on gross investment in nonresidential structures, producers' durable equipment, and residential structures from the NIPA Table 5.5 to construct the corresponding components of the gross capital stocks. Likewise, quarterly data on the consumption of fixed capital, NIPA Table 1.10, and the rental income of persons with capital consumption adjustment, NIPA Table 1.14, were used to derive quarterly measures of depreciation for the fixed private nonresidential and residential capital stocks, respectively. Finally, quarterly series of the net stock of government owned fixed capital was linearly interpolated from the annual measure using the quarterly stock of fixed private nonresidential capital.[11]

The share of labor in national income denoted α_t is constructed as the ratio of total employee compensation to national income, NIPA Table 1.14. To calculate the labor share in costs denoted α_t^c, an estimate of the rental rate of capital is required. Following Hall and Jorgenson (1967), this is calculated as:

$$r_t = (\delta + v_t)\frac{1 - z_t\tau_t - \omega_t}{1 - \tau_t}p_{kt};$$

where δ is the average depreciation rate, v_t is the required rate of return on capital (measured as

[11] Our constructed measure of the physical capital is similar to that used by Christiano (1988) and Burnside, Eichenbaum, and Rebelo (1995) except for the fact that it excludes the stock of consumer durables.

the dividend yield on the Standard and Poor 500 portfolio), z_t is the present discounted value of depreciation allowances, ω_t is the investment tax credit rate, τ_t is the profits tax rate, and p_{kt} is the deflator for business fixed investment, NIPA Table 7.1. The value of δ was taken to be 0.021. We obtained unpublished data on the present discounted value of depreciation allowances z_t, the investment tax credit ω_t and current value of the capital stocks of corporate and noncorporate capital from Dale Jorgenson. We constructed an aggregate cost of capital variable by weighting the cost of capital for each sector by the current value of the stocks of corporate and noncorporate capital. The average marginal tax rates used to construct the cost of capital variables are from Jorgenson and Yun (1995).

The calculation of the Solow residuals depends on the particular specification that is used. For example, the Solow residual for the benchmark model is computed as $\Delta \ln(z_t^1)$ from equation (2.4). We replace α_t by $\bar{\alpha}_t = .5(\alpha_t + \alpha_{t-1})$ in all the relevant expressions to obtain a Tornquist index of multi-factor productivity. We omitted observations on all the series prior to 1953 to obtain a sample of 163 observations, from 1953:I to 1993:III.

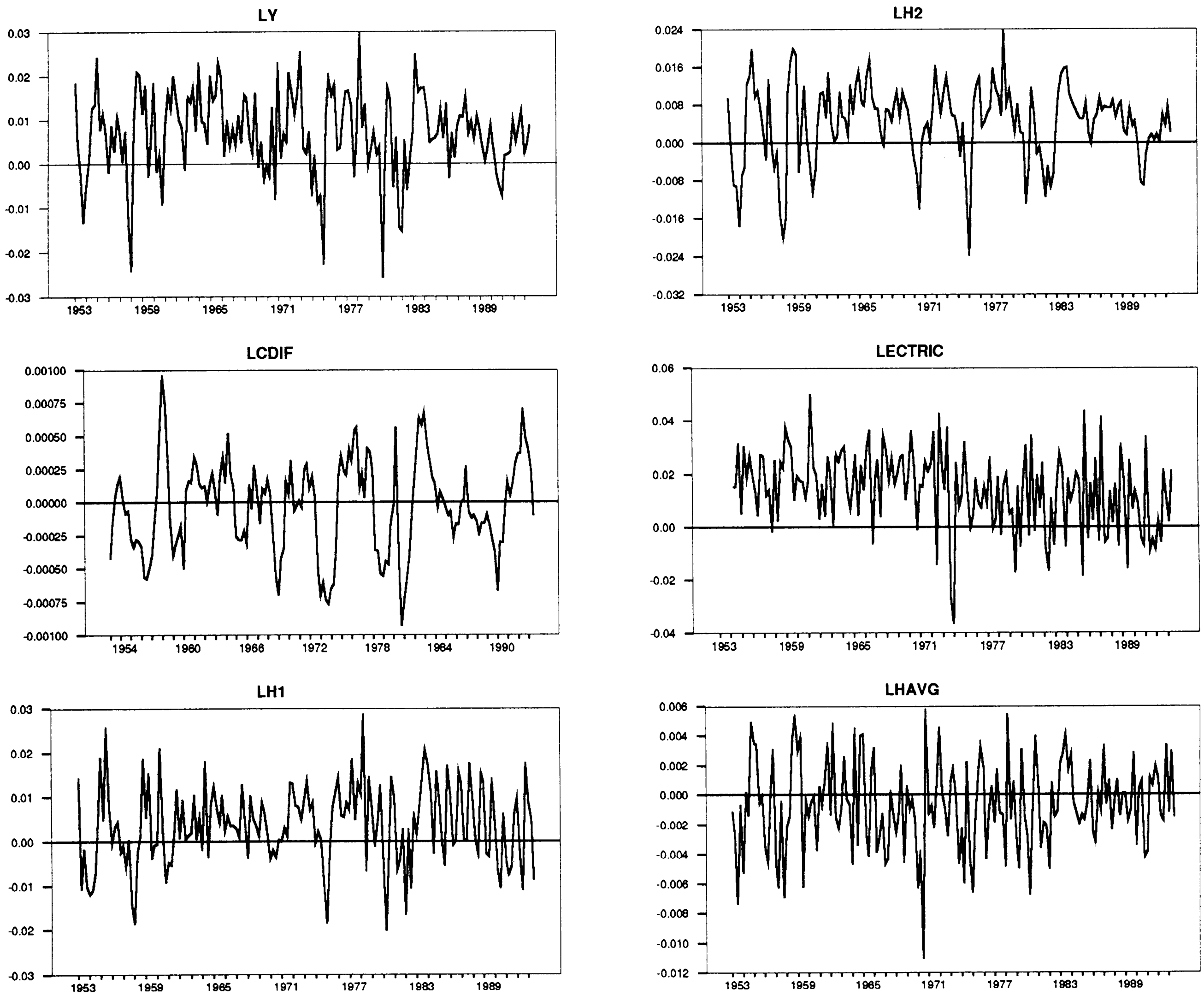

Figure 1

Time plots of the six observable series.

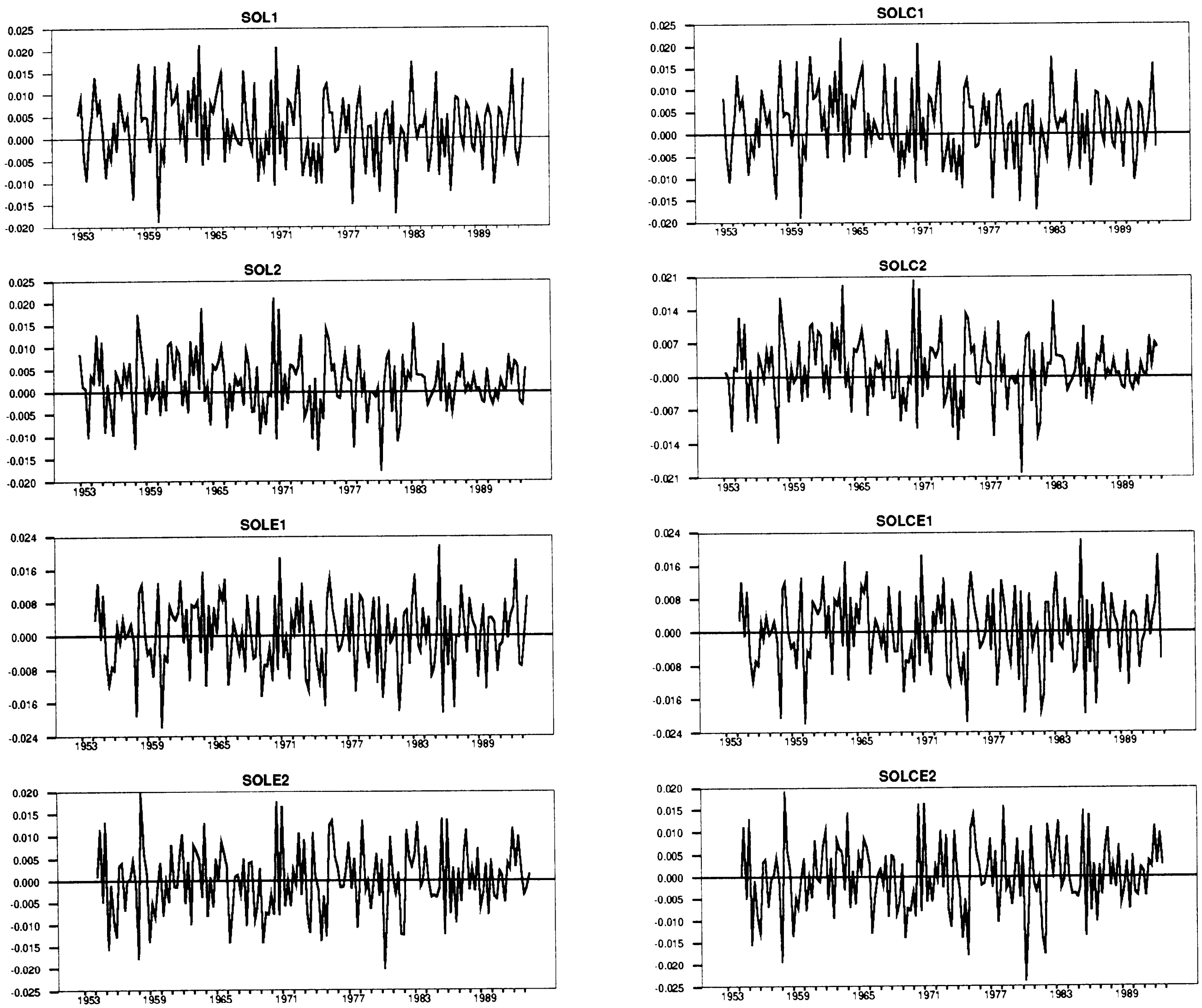

Figure 2

Time plots of the eight derived Solow residuals.

Table 1 { Variable Names and De¯nitions

This Table de¯nes all the variables in the text. The Appendix contains a further description of how each of these variables is constructed.

LY: growth rate of real GNP
LH1: growth rate of hours worked for all workers, all industries
LH2: growth rate of employee-hours in nonagricultural establishments
LC: growth rate of physical capital stock
LCDIF: di®erences of growth rate of physical capital stock
LECTRIC: growth rate of electricity usage
LHAVG: growth rate of average hours per worker
SHARE: share of labor in total income
SHAREC: share of labor in total costs
SOL1: LY- SHARE*LH1 -(1-SHARE)*LC
SOL2: LY- SHARE*LH2 -(1-SHARE)*LC
SOLE1: LY- SHARE*LH1 -(1-SHARE)*LECTRIC
SOLE2: LY- SHARE*LH2 -(1-SHARE)*LECTRIC
SOLC1: LY- SHAREC*LH1 -(1-SHAREC)*LC
SOLC2: LY- SHAREC*LH2 -(1-SHAREC)*LC
SOLCE1: LY- SHAREC*LH1 -(1-SHAREC)*LECTRIC
SOLCE2: LY- SHAREC*LH2 -(1-SHAREC)*LECTRIC

Table 2 – Hinich Bicovariance and McLeod-Li Test Results[a]

This Table summarizes the results using the Hinich bicovariance test and the McLeod-Li test. The tests are applied to the real output (LY), capital stock (LCDIF), and hours worked (LH1 and LH2) series and also to the two implied Solow residual series – SOL1 and SOL2. Definitions of these series are in the Appendix. The McLeod-Li test results are reported for lags $k = 1, 2, 3, 4$, and 8; the Hinich bicovariance test uses $\ell = 7$. These tests are described in Section 3.

Test	Output (growth rate) LY	Capital (growth rate) LCDIF	Labor			
			hours worked, all industries		employee hours, nonagric. est.	
			(growth rate) LH1	implied Solow residual SOL1	(growth rate) LH2	implied Solow residual SOL2
Hinich bicovariance	0.012^{*}	0.605	0.018^{*}	0.404	0.000^{**}	0.088
McLeod-Li						
1	0.407	0.601	0.939	0.704	0.172	0.466
2	0.229	0.868	0.718	0.869	0.047^{*}	0.397
3	0.344	0.829	0.667	0.243	0.038^{*}	0.380
4	0.416	0.918	0.541	0.306	0.014^{*}	0.543
8	0.191	0.380	0.526	0.650	0.015^{*}	0.867

[a] Significance level at which null hypothesis of linear generating mechanism can be rejected, based on 1000 bootstrap replications generated using 163 pre-whitened observations from 1953:I to 1993:III. Results which are significant at the 5% and 1% levels are marked with a * and **, respectively.

Table 3 { BDS Test Results[a]

This Table summarizes the results using the BDS test. The tests are applied to the real output (LY), capital stock (LCDIF), and hours worked (LH1 and LH2) series and also to the two implied Solow residual series { SOL1 and SOL2. De¯nitions of these series are in the Appendix. The BDS test is described in Section 3; ² is the sup norm on the m-histories, m is the embedding dimension.

²	m	Output (growth rate) LY	Capital (growth rate) LCDIF	Labor			
				hours worked, all industries		employee hours, nonagric. est.	
				(growth rate) LH1	implied Solow residual SOL1	(growth rate) LH2	implied Solow residual SOL2
0.5	2	0.359	0.531	0.582	0.434	0:002¤¤	0.154
0.5	3	0.221	0.345	0.285	0.441	0:001¤¤	0.091
0.5	4	0.365	0.395	0.059	0.712	0:002¤¤	0.123
1.0	2	0.363	0.635	0.163	0.876	0:006¤¤	0.243
1.0	3	0:037¤	0.755	0.080	0.809	0:000¤¤	0.154
1.0	4	0:023¤	0.775	0.053	0.878	0:000¤¤	0.133
2.0	2	0.203	0.378	0.186	0.607	0.092	0.119
2.0	3	0:040¤	0.511	0.095	0.566	0:019¤¤	0.079
2.0	4	0:022¤	0.626	0.144	0.730	0:006¤¤	0.092

[a] Signi¯cance level at which null hypothesis of linear generating mechanism can be rejected, based on 1000 bootstrap replications generated using 163 pre-whitened observations from 1953:I to 1993:III. Results which are signi¯cant at the 5% and 1% levels are marked with a ¤ and ¤¤, respectively.

Table 4 { Hinich Bicovariance and McLeod-Li Test Results[a]

This Table summarizes the results using the Hinich bicovariance test and the McLeod-Li test. The tests are applied to the electricity usage (LECTRIC), average hours worked per worker (LHAVG) and six Solow residual series { SOLE1 through SOLCE2. De¯nitions of these series are in the Appendix. The McLeod-Li test results are reported for lags $k = 1; 2; 3; 4$, and 8; the Hinich bicovariance test uses $` = 7$. These tests are described in Section 3.

Test	Electricity usage (growth rate) LECTRIC	Average hours per worker (growth rate) LHAVG	Solow residuals					
			SOLE1	SOLE2	SOLC1	SOLC2	SOLCE1	SOLCE2
Hinich bicovariance	0.808	$0{:}045^{¤}$	0.342	0.147	0.362	0.065	0.354	0.086
McLeod-Li								
1	0.241	0.512	0.620	0.323	0.709	0.981	0.461	0.195
2	0.438	0.700	0.660	0.613	0.915	0.771	0.707	0.350
3	0.197	0.640	0.616	0.819	0.304	0.893	0.689	0.441
4	0.112	0.800	0.360	0.571	0.417	0.710	0.332	0.492
8	0.246	0.879	0.498	0.521	0.621	0.902	0.461	0.682

[a] Signi¯cance level at which null hypothesis of linear generating mechanism can be rejected, based on 1000 bootstrap replications generated using 163 pre-whitened observations from 1953:I to 1993:III. Results which are signi¯cant at the 5% and 1% levels are marked with a ¤ and ¤¤, respectively.

Table 5 – BDS Test Results[a]

This Table summarizes the results using the BDS test. The tests are applied to the electricity usage (LECTRIC), average hours worked per worker (LHAVG) and six Solow residual series – SOLE1 through SOLCE2. Definitions of these series are in the Appendix. The BDS test is described in Section 3; ϵ is the sup norm on the m-histories, m is the embedding dimension.

ϵ	m	Electricity usage (growth rate) LECTRIC	Average hours per worker (growth rate) LHAVG	Solow residuals					
				SOLE1	SOLE2	SOLC1	SOLC2	SOLCE1	SOLCE2
0.5	2	0.107	0.655	0.945	0.257	0.360	0.859	0.840	0.174
0.5	3	0.294	0.856	0.940	0.107	0.610	0.831	0.914	0.130
0.5	4	0.199	0.920	0.891	0.153	0.646	0.893	0.975	0.056
1.0	2	0.125	0.600	0.558	0.285	0.743	0.742	0.381	0.264
1.0	3	0.149	0.526	0.622	0.159	0.826	0.569	0.543	0.304
1.0	4	0.242	0.343	0.709	0.117	0.795	0.428	0.546	0.184
2.0	2	0.170	0.673	0.270	0.125	0.488	0.597	0.229	0.074
2.0	3	0.231	0.716	0.320	0.077	0.571	0.448	0.387	0.071
2.0	4	0.380	0.433	0.426	0.057	0.643	0.295	0.518	0.057

[a] Significance level at which null hypothesis of linear generating mechanism can be rejected, based on 1000 bootstrap replications generated using 163 pre-whitened observations from 1953:I to 1993:III. Results which are significant at the 5% and 1% levels are marked with a * and **, respectively.

Table 6 — Palm/Pfann (1997) Asymmetric Adjustment Cost Model Test Results: Quadratic Real Factor Prices External Driving Process[a]

This table summarizes the results using the Hinich bicovariance test, the McLeod-Li test, and the BDS test. The tests are applied to the simulated real output (Y), capital stock (K), and employment (L) series from the Palm/Pfann (1997) asymmetric adjustment cost model with a quadratic real factor prices external driving process. The McLeod-Li test results are reported for lags $k = 1, 2, 3, 4$, and 8; the Hinich bicovariance test uses $\ell = 10$. These tests are described in Section 3.

Test	Output (growth rate) Y	Capital (growth rate) K	Labor (growth rate) L
Hinich bicovariance	0.311	0.000**	0.428
McLeod-Li			
1	0.714	0.000**	0.691
2	0.086	0.000**	0.870
3	0.140	0.000**	0.937
4	0.140	0.000**	0.969
8	0.257	0.000**	0.901

Test		Output (growth rate) Y	Capital (growth rate) K	Labor (growth rate) L
BDS				
ϵ	m			
0.5	2	0.109	0.000**	0.634
0.5	3	0.062	0.000**	0.613
0.5	4	0.055	0.000**	0.336
1.0	2	0.189	0.000**	0.411
1.0	3	0.088	0.000**	0.422
1.0	4	0.038*	0.000**	0.254
2.0	2	0.406	0.000**	0.264
2.0	3	0.195	0.000**	0.217
2.0	4	0.158	0.000**	0.184

[a] Based on 355 simulated observations, using five simulation runs of 71 observations each. After an adjustment for differing sample variances, the data were reasonably stationary across the simulations.

Table 7 — Palm/Pfann (1997) Asymmetric Adjustment Cost Model Test Results: Linear Real Factor Prices External Driving Process[a]

This table summarizes the results using the Hinich bicovariance test, the McLeod-Li test, and the BDS test. The tests are applied to the simulated real output (Y), capital stock (K), and employment (L) series from the Palm/Pfann (1997) asymmetric adjustment cost model with a linear real factor prices external driving process. The McLeod-Li test results are reported for lags $k = 1, 2, 3, 4$, and 8; the Hinich bicovariance test uses $\ell = 10$. These tests are described in Section 3.

Test	Output (growth rate) Y	Capital (growth rate) K	Labor (growth rate) L
Hinich bicovariance	0.033^{*}	0.000^{**}	0.093
McLeod-Li			
1	0.007^{**}	0.000^{**}	0.267
2	0.000^{**}	0.000^{**}	0.512
3	0.001^{**}	0.000^{**}	0.152
4	0.001^{**}	0.000^{**}	0.156
8	0.002^{**}	0.000^{**}	0.379

Test: BDS ϵ	m	Output (growth rate) Y	Capital (growth rate) K	Labor (growth rate) L
0.5	2	0.000^{**}	0.000^{**}	0.271
0.5	3	0.000^{**}	0.000^{**}	0.115
0.5	4	0.000^{**}	0.000^{**}	0.047^{*}
1.0	2	0.000^{**}	0.000^{**}	0.312
1.0	3	0.000^{**}	0.000^{**}	0.156
1.0	4	0.000^{**}	0.000^{**}	0.083
2.0	2	0.001^{**}	0.000^{**}	0.832
2.0	3	0.000^{**}	0.000^{**}	0.713
2.0	4	0.000^{**}	0.000^{**}	0.582

[a] Based on 355 simulated observations, using five simulation runs of 71 observations each. After an adjustment for differing sample variances, the data were reasonably stationary across the simulations.