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STOCHASTIC TRENDS AND ECONOMIC FLUCTUATIONS

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ABSTRACT

Recent developments in macroeconomic theory emphasize that transient economic fluctuations can arise as responses to changes in long run factors -- in particular, technological improvements -- rather than short run factors. This contrasts with the view that short run fluctuations and shifts in long run trends are largely unrelated. We examine empirically the effect of shifts in stochastic trends that are common to several macroeconomic series. Using a linear time series model related to a VAR, we consider first a system with GNP, consumption and investment with a single common stochstic trend; we then examine this system augmented by money and prices and an additional stochastic trend. Our results suggest that movements in the "real" stochastic trend account for one-half to two-thirds of the variation in postwar U.S. GNP.

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1. Introduction

The dichotomy between trend and cycle has played an important role in both classical and Keynesian analyses of economic fluctuations. The prevailing view seems to be that fluctuations arise from temporary disturbances that are sometimes associated with variations in monetary and fiscal policies. These shocks are then propagated by the economic system in ways that result in systematic patterns of persistence and co-movements among key economic series. Secular trends, while also related across series, are viewed as evolving slowly through time and having little influence on the quarter-to-quarter or year-to-year variations in economic conditions. This view, compounded by a lack of statistical techniques for investigating stochastically trending variables, has dominated macroeconomic research.

Empirical evidence presented by Nelson and Plosser (1982) and others questions the validity of this traditional dichotomy. They find that the long-run character of many economic time series is well described as a stochastic trend or a random walk (typically with drift). Moreover, they present some evidence that innovations in the stochastic trend may account for a significant portion of the short-run, as well as the long-run, variation in such key series as real GNP. A shortcoming of the Nelson and Plosser (1982) and related analyses is the reliance on univariate time series methods. In particular, as we shall argue below, both empirical and theoretical findings point to the existence of a reduced number of stochastic trends that are common to many key economic variables. The earlier research into the univariate properties of macroeconomic variables cannot address questions concerning the interrelation among stochastic trends or whether innovations in the stochastic trends induce short-run "business cycle" behavior.

The purpose of this paper is to develop the concept of common stochastic trends in the context of a simple equilibrium model and to present a statistical analysis of the importance of these common trends. In Section 2, we provide an economic model that exhibits a single common stochastic trend. This common trend has the interpretation of a permanent productivity disturbance that alters the steady state equilibrium of the economy. This disturbance also accounts for nontrivial dynamics of individual series as they adjust towards the new steady state.

In Section 3, we describe an empirical methodology for analyzing multivariate time series that possess common trends. This approach is designed to answer two questions. First, is there evidence that aggregate time series variables are characterized by a reduced number of common stochastic trends? Second, to what extent do innovations in these permanent trends account for short-run as well as long-run movements in key aggregate variables? Our techniques are VAR methods -- modified for use with cointegrated variables as outlined by Engle and Granger (1987) -- that explicitly incorporate common stochastic trends. While this analysis is motivated by the equilibrium model of Section 2, the time series techniques are quite general and permit short run dynamic behavior that could in principle be consistent with a wide variety of economic mechanisms.

Section 4 presents a simple three-variable empirical model focusing on measures of output, consumption, and investment. In Section 5, we extend this analysis to include money and prices, identifying one real and one nominal permanent shock to the economy. In Section 6, we examine more closely the permanent components of GNP predicted by our five-variable model, along with the estimated real and nominal permanent shocks. In particular, we compare the innovations in the real permanent component in our five-variable model to two variants of Solow's (1957) measure of changes in total factor productivity. Our conclusions are summarized in Section 7.

2. Growth and Fluctuations: A Stylized Model

An important recent line of macroeconomic research involves the modeling of economic fluctuations as competitive equilibrium outcomes, frequently those of a large number of representative agents. It remains an open question whether this paradigm and, more particularly, the versions of it that stress that the principal disturbances to the economy are real in nature (e.g. Kydland and Prescott [1982] and Long and Plosser [1983]) are reasonably accurate empirical descriptions of actual aggregate time series. However, from the standpoint of this paper, the key feature of this approach is that it provides a unified framework for examining long run growth, short run fluctuations, and the interactions between these two phenomena.

Within the general real business cycle approach, we identify two distinct hypotheses. The first is that economic fluctuations -- serially correlated variations in the level of economic activity -- arise from *transitory* shocks to production possibilities, with observed fluctuations being persistent because the internal mechanisms of the economy "propagate" the disturbances over time (see Long and Plosser [1983]). This corresponds to a conventional view of economic fluctuations that is embedded in many other theories, including natural rate models of both Keynesian and neoclassical varieties that emphasize the role of nominal impulses (e.g. Fischer [1977] and Phelps and Taylor [1977] or Lucas [1973] and Barro [1976]).

A second hypothesis in real business cycle models is that economic fluctuations are the response of the economy to *permanent* changes in underlying technology (as in Long and Plosser [1983], Hansen [1986] or Christiano [1986]). In a certainty equivalence presentation of this view, permanent shifts in technology occasion changes in the "steady-state" levels of capital stocks, and economic fluctuations are essentially movements along the adjustment path to the new steady-state. It is this second hypothesis -- that persistent random changes in technology account for a dominant component of short-run changes in economic activity -- that we investigate here.

A Neoclassical Model with Permanent Technology Shocks

We motivate our empirical investigation by considering a neoclassical macroeconomic model that incorporates permanent shocks to the level of total factor productivity. Suppose that there are many identical agents in this economy. Since no trade will be possible in equilibrium, and in the absence of taxes or productive externalities, we may compute competitive quantities by the device of solving the problem for a representative agent who directly operates the production technology. Decentralization to individual decision-making is direct since equilibrium prices can be found from the relevant marginal rates of substitution for the representative agent at optimal quantities.

Preferences and endowments. Agents value sequences of consumption $\{C_t\}$ and leisure $\{L_t\}$ according to a time-separable utility function of the form,

$$(2.1) \qquad U_t = \sum_{j=t}^{\infty} \beta^{j-t} u(C_{t+j}, L_{t+j})$$

where $0<\beta<1$. The representative individual begins period t with the capital stock (K_t) and possesses an endowment of time, normalized to one in each period.

Production possibilities. There are standard neoclassical specifications for the point-in-time and intertemporal production possibilities. Date t commodity output is produced according to a Cobb-Douglas production function with constant returns to scale,

$$(2.2) \qquad Y_t = \lambda_t K_t^{1-\theta} N_t^{\theta}$$

where N_t is the units of labor effort employed and λ_t is an exogenous stochastic process for total factor productivity that we will discuss further below. Capital accumulation takes place according to the simple evolution equation,

$$(2.3) \qquad K_{t+1} = (1-\delta)K_t + I_t \ .$$

The representative agent faces two resource constraints, one on goods, $C_t+I_t \le Y_t$, and one on time, $N_t+L_t \le 1$.

Technology shocks. The exogenous process for total factor productivity λ_t is given by a logarithmic random walk,

$$(2.4) \qquad \log(\lambda_t) = \mu + \log(\lambda_{t-1}) + \eta_t$$

where the innovation η_t is taken to be independently and identically distributed with mean zero and variance σ^2. Thus the average growth rate of total factor productivity is μ, although in any period the actual growth rate will deviate from μ by some unpredictable amount η_t.

Restrictions. We are interested in studying the outcomes of this model under restrictions which imply that there is steady-state growth under certainty. As discussed by King, Plosser and Rebelo (1986), these imply that, if it is separable in its arguments, then the utility function u(•) has the form,

$$u(C_t,L_t) = \log(C_t) + v(L_t) \ . \tag{2.5}$$

This specification, which we henceforth assume, implies that the income and substitution effects of the trend growth in λ_t (through the drift μ) are exactly offsetting on leisure. This is a necessary condition for a stochastic steady state, since total hours are bounded.

Analysis of Dynamics. Following King and Rebelo's (1986) approach to the analysis of economies with stochastic steady states, it is most direct to transform the model to one that possesses a stationary distribution. The transformations are analogous to those employed in the theory of growth under certainty. Specifically, let

$$k_t = (K_t)/(\lambda_t)^{1/\theta} \qquad i_t = (I_t)/(\lambda_t)^{1/\theta} \qquad c_t = (C_t)/(\lambda_t)^{1/\theta} \ . \tag{2.6}$$

Technically, these transformations permit us to restate the problem as a stationary one. Their form can best be understood by considering the conditions for a certainty steady state growth path. In this situation, the capital stock must adjust so that the net rate of return equals the pure rate of time preference, which implies that $\beta[\lambda_t(1-\theta)K^{-\theta}N^{\theta}+(1-\delta)]=1$ in steady state. Thus, with effort invariant in the long run, a 1% rise in λ must eventually induce a $1/\theta$ percent increase in K to restore this equality. That is, these transformations entail removing the long run effects of the stochastic disturbances.

With these definitions, it follows that this economy is related to one with a stochastic depreciation rate on capital, for which the choice problem for the individual is to maximize

$$E \sum_{j=t}^{\infty} \beta^{j-t}[\log(c_{t+j}) + v(L_{t+j}) + (1/\theta)\log(\lambda_{t+j})]$$

$$\text{subject to:} \quad \begin{aligned} & c_t + i_t \leq k_t^{1-\theta}N_t^{\theta} \\ & N_t + L_t \leq 1 \\ & k_{t+1} = [(1-\delta)k_t + i_t]\exp[-(\mu+\eta_{t+1})/\theta] \ . \end{aligned}$$

The optimal decision rules for this transformed environment have the general form,

$$\begin{aligned} & i_t = i(k_t) \\ & c_t = c(k_t) \\ (2.7) \qquad & N_t = N(k_t) \\ & y_t = k_t^{1-\theta}N(k_t)^{\theta} \\ & k_{t+1} = [(1-\delta)k_t + i(k_t)]\exp[-(\mu+\eta_{t+1})/\theta] \ . \end{aligned}$$

Under mild conditions on η_t, then transformed capital stock k_t possesses a stationary distribution (see Brock and Mirman [1972]), so that all of the variables c_t, i_t, N_t, and y_t are stationary as well.

Although the transformed variables are stationary, in log levels they are not. Transforming to logarithms, the economy evolves according to

$$
\begin{aligned}
\log(K_{t+1}) &= \tau_t + \log[(1-\delta)k_t+i(k_t)] \\
\log(Y_t) &= \tau_t + \{(1-\theta)\log(k_t) + \theta\log(N(k_t))\} \\
\log(C_t) &= \tau_t + \log(c(k_t)) \\
\log(I_t) &= \tau_t + \log(i(k_t)) \\
\log(N_t) &= \log(N(k_t))
\end{aligned}
\tag{2.8}
$$

where $\tau_t=(1/\theta)\log(\lambda_t)$. Thus the levels of consumption, investment and output are nonstationary in levels in this economy -- due to persistent technological change -- but certain transformations of these variables are stationary when a stochastic steady state exists. This structure means that conventional econometric techniques of time series analysis, such as log-linearly detrending the data and treating the residuals as a stationary stochastic process, will not be appropriate for data generated by this economy because the time series contain random walk components due to their common dependence on technology. In the sections below, we consider some econometric techniques that are appropriate for data generated by such economies, exploiting the natural linkages between stationarity of transformations of variables in the theoretical structure (2.8) and recent developments in methods for analyzing cointegrated processes.

Two general properties of this framework deserve emphasis. First, there is a single source of nonstationarity -- a common "stochastic trend" -- implied by this model. The logarithm of each of the non-stationary time series (Y, C, I and K) can be represented as the sum of a random walk (τ_t) and a serially correlated, but stationary series. For example, in addition to its random walk component, consumption includes a stationary component, $\log(c(k_t)))$. Second, the permanent and stationary components are both functions of the single technology shock (η_t). Third, the stationary components will generally be serially correlated because transformed capital is Markov, i.e. $\log(k_{t+1})=\log[(1-\delta)k_t+i(k_t)]-(1/\theta)\Delta\log\lambda_{t+1}$. As in the standard neoclassical growth model of Brock and Mirman (1972), a Markovian law of motion for capital arises from the desire of individuals to smooth the influence of transitory shocks to production opportunities. This smoothing behavior also implies that the stationary component of consumption ($\log[c(k_t)]$) is also Markov.

The economic mechanisms at work in generating these key features are readily developed by considering how the model economy responds to a positive change in technology under certainty equivalence. Since the level of the production function is permanently higher after the productivity improvement, there will be a new, higher steady-state capital stock and associated increased flows of consumption, investment and output. However, capital does not immediately jump to the new higher level, since that would entail too large a burden on current consumption. Rather, as we know from the neoclassical model with fixed labor, there is a transition period during which capital is built up (since transformed capital k is low relative to its steady-state value).

The addition of labor permits society to vary this input along the transition path. Simulations by King, Plosser and Rebelo (1986, Section 6) indicate that, for commonly employed specifications of preferences, hours will rise in response to a permanent technology shock -- yielding additional production along the transition path -- before settling back to the invariant long-run level. One might think that the intertemporal substitution response would act in the opposite direction (since the marginal product of labor is now low), but this neglects the fact that a permanent technology shock raises the real rate of return on investment opportunities.[1]

Taking the Model to the Data

This stylized model is clearly too simple to describe the data from any actual economy. For example, the aggregate time series in (2.8) are driven by a single shock, so that the matrix of one-step ahead forecast errors would be singular for data generated by this economy. Thus, prior to econometric implementation, it is necessary to introduce additional disturbances. In addition, since it encompasses only real variables, the model economy developed above is not well suited for studying time series data from any actual economy, since exchanges in modern economies are undertaken in nominal terms.[2] Nevertheless, in Section 4 we study a small multivariate system of real aggregates. Then, in Section 5, we consider a system augmented to include money and prices. To rationalize this exclusion of nominal variables in Section 4, it is useful to think of appending a money demand function and "Fisher equation" to the preceding model economy. Thus, monetary developments will be neutral by construction. However, additional stochastic trends may enter through a variety of channels: (a) through the money supply, which is difference stationary in the univariate analysis of Nelson and Plosser (1982);

or (b) through the demand for money (or, equivalently, its velocity of circulation), which could reflect more fundamental trends in currency usage or technological changes in the banking sector.

3. Empirical Framework

This section presents our statistical procedures for assessing empirically the number and quantitative importance of permanent disturbances. One approach to investigating these issues is to pursue explicit formulations of theoretical models and to test the implied restrictions. We do not follow this strategy since those models that are analytically tractable are very restrictive. Instead, we propose a general statistical model, which is likely to be useful in a variety of circumstances, that involves a linear decomposition of a vector of time series into nonstationary and stationary components.

The Common Trends Model

We consider a general factor model representation of an n-dimensional vector X_t, where the common factors are random walks. This "common trends" model is written as

$$X_t = \gamma + A\tau_t + D(L)\epsilon_t, \qquad \tau_t = \mu + \tau_{t-1} + \eta_t \tag{3.1}$$

where γ is a n×1 vector of constants, τ_t is a k×1 vector of random walks with drift μ and innovations η_t (where k≤n), L is the lag operator, D(L) is a n×n

matrix of lag polynomials, and ϵ_t is a n×1 vector of serially uncorrelated, mean zero transitory innovations with covariance matrix Σ. The lag polynomial D(L) is assumed to decay sufficiently rapidly that $\sum_{j=0}^{\infty}|D_j|$ is finite, from which it follows that the elements of $D(L)\epsilon_t$ have finite variances and are stationary. The "factor loading" matrix A has dimension n×k, and is assumed to have full column rank.

The formulation (3.1) decomposes the vector X_t into permanent and transitory components. While $D(L)\epsilon_t$ is stationary, $A\tau_t$ is not: in the long run, X_t will track this stochastic trend, up to the transient deviation $D(L)\epsilon_t$. Thus $X_t^p = A\tau_t$ can be thought of as the permanent component of X_t, while $X_t^s = D(L)\epsilon_t$ can be thought of as a stationary or transient component. That is,

$$X_t = \gamma + X_t^p + X_t^s \,. \tag{3.2}$$

Moreover, if the number of stochastic trends (k) is less than the number of variables but each element of X_t individually contains a stochastic trend, then, in the long run, some elements of X_t will move together. More precisely, if $k<n$, then there is a $n\times(n-k)$ matrix α with rows such that $\alpha'A=0$. From this observation and (3.2), it follows that $\alpha'X_t = \alpha'\gamma+\alpha'X_t^s$, i.e. there are n-k linear combinations of contemporaneous values of X_t that are stationary, even though each element of X_t itself is dominated by a unit root. But this is just Engle and Granger's (1987) definition of cointegration: in the common trends model with k common trends, X_t will be cointegrated with n-k cointegrating vectors given by the columns of α.

Factor models typically require additional restrictions on the relation

between the innovations in the two components. Nevertheless, the fact that one of the components in (3.1) is nonstationary while the other is stationary means that certain features of (3.1) can be investigated without imposing additional restrictions. First, because X_t^p is nonstationary and X_t^s is stationary, the optimal estimate of X_t^p using current and lagged values of X_t does not depend (asymptotically) on the relation between the permanent and transitory innovations (see Watson [1986])[3]. In particular, as noted by Beveridge and Nelson (1981) for the univariate case, optimal estimates of X_t^p can be obtained from the long run forecast of X_t adjusted for deterministic growth. Since X_t^s is a stationary, mean zero process, it can have no influence asymptotically on the long-run level of a nonstationary series. Thus the optimal estimates of $A\tau_t$ are invariant to the correlation between the permanent and transitory innovations.

Second, in addition to the behavior of $A\tau_t$, we are also interested in knowing the number of common stochastic trends, i.e. the dimensionality of τ_t. For the same intuitive reason that the long run forecasts are independent of the relation between the short run and long run innovations, it is possible to address this issue statistically without further restrictions on the correlation between the permanent and transitory innovations. This has two immediate consequences for our investigation. First, the cointegrating vectors α can be estimated consistently under weak assumptions on $D(L)\epsilon_t$, without imposing additional restrictions or identifying assumptions on (3.1) (Stock [1984]); a simple way to estimate the cointegrating vectors is to run a series of contemporaneous ordinary least squares regressions. Second, testing for the number of cointegrating vectors is equivalent to testing for the number of common stochastic trends. These tests are valid under the same weak conditions that ensure consistent estimation of the cointegrating vectors. The specific tests we use, developed in Stock and Watson (1986), are discussed in more detail below. Summarizing, statistical procedures can be used to ascertain the dimensionality of τ_t and to estimate α and $X_t^P = A\tau_t$ without restricting the correlation structure between η_t and ϵ_t.

Estimation of other statistics of interest requires additional identifying assumptions. First, consider the problem of estimating the factor loading matrix A. Since $\alpha'A=0$, then either estimated or theoretical cointegrating vectors can be used to construct some estimate of A. However, this estimate will not be unique: if $\alpha'A=0$, then $\alpha'AR=0$, where R is any k×k matrix. Another way to see this problem is to recall from the discussions above that we are only able to identify $A\tau_t$ and k. Thus, A and τ_t are only identified up to an arbitrary transformation by a k×k matrix R, since $A\tau_t = ARR^{-1}\tau_t \equiv A^*\tau_t^*$. If k=1, R is a scalar, and this choice simply amounts to suitably normalizing the variance of η_t. However, if k>1, the choice of a (nonsingular) transformation R that decomposes X_t^P into A and τ_t cannot be made purely on statistical grounds, since all such transformations are observationally equivalent. Rather, the choice must be based on some *a-priori* considerations that generally involve economic theory. The second empirical model presented below contains two common trends, and our choice of normalization is discussed extensively at that point.

A second set of statistics of interest describe the dynamic properties of (3.1), such as the response of X_t to a unit innovation in the permanent component η_t or the fraction of the variation in the forecast errors of X_t attributable to the individual permanent components. Interpreting these statistics requires additional identification assumptions that are central to assessing the implications of the permanent innovations for short run fluctuations. For example, if it is assumed (as often it is in unobserved component models) that the permanent and transitory disturbances are mutually uncorrelated ($E\epsilon_{t-s}\eta_t'=0$ for all s), then a permanent disturbance would have no dynamic implications beyond a one-time shift in X_t as captured by A. The permanent shocks would then have no affect on the stationary component of X_t thereby excluding the sorts of dynamic responses to permanent technology shocks present in the theoretical models of Section 2.

An alternative approach to imposing additional restrictions on (3.1) would be to take a more specific structure, explicitly derived from economic theory, and to impose the implied restrictions. This presents different problems. For example, in the model of Section 2, there is only one disturbance, so the process is singular and the innovations in the permanent and stationary components are perfectly correlated. To implement such a model would require either including additional sources of noise to the structural model or, as in Altug (1984), recognizing that the aggregate time series variables are measured with error. The first approach amounts to working with fully specified structural models which, for reasons discussed above, is not a particularly attractive alternative at the current stage of research. On the other hand, the second approach requires taking an explicit stand on the sources and character of the measurement errors.[4]

We adopt a third approach that results in a computationally simpler estimation technique and permits the permanent and transitory innovations to be correlated. This formulation has its roots in the stationary/nonstationary decomposition of univariate time series by Beveridge and Nelson (1981) and the cointegrated models of Engle and Granger (1987). It was argued above that if

X_t has a common trends representation, then it is cointegrated. In the Appendix, it is shown that if X_t is cointegrated, then it has a common trends representation of the form (3.1), where $\eta_t = F\epsilon_t$, where F is a k×n matrix, and where ϵ_t corresponds to the innovations in the Wold moving average representation of $\Delta X_t=(1-L)X_t$,

$$(3.3) \qquad \Delta X_t = \delta + C(L)\epsilon_t$$

where $\alpha'C(1)=0$. Our specific common trends model is derived from (3.3), just as the Beveridge-Nelson (1981) decomposition of a univariate series into permanent and transitory components can be derived from a univariate version of (3.3). The correlation between any permanent innovation η_t and the transitory innovations ϵ_t is not restricted *a-priori*, but rather depends on F. However, in this formulation the vector of permanent innovations is completely determined by the vector of transitory innovations.

It is well known that the interpretation of impulse responses to linear combinations of errors in stationary multivariate time series models such as conventional vector autoregressions (VAR's) depends on additional identification assumptions on the underlying innovations, say that they are orthogonal and ordered according to a specific Wold causal structure. Similar issues arise here, except that the identification requirements are reduced by the assumption that X_t is cointegrated. Specifically, suppose that $\eta_t^{\dagger}=F^{\dagger}\epsilon_t$, where $F^{\dagger}$ is some nonsingular n×n matrix, $\eta_t^{\dagger}=(\eta_t' \ \tilde{\eta}_t')'$ is a n×1 vector of transformed innovations with η_t the k×1 vector of permanent innovations, and where x' denotes the transpose of x. Similarly letting $C^{\dagger}(L)=C(L)F^{\dagger -1}$, (3.3) can be rewritten,

$$(3.4) \qquad \Delta X_t = \delta + C(L)(F^{\dagger})^{-1}F^{\dagger}\epsilon_t = \delta + C^{\dagger}(L)\eta_t^{\dagger} \quad .$$

Computation of impulse response functions or variance decompositions requires making sufficient assumptions to estimate $F^{\dagger}$. In the common trends model, the first k rows of $F^{\dagger}$, F, are determined from the long-run properties of the model (essentially by the cointegrating vectors); the identification conditions needed to estimate A suffice for the estimation of F. However, the first k columns of $C^{\dagger}(L)$, and thus the impulse responses and variance decompositions with respect to the permanent innovations η_t, will depend in part on the final n-k rows of $F^{\dagger}$. Thus, in computing the impulse responses we make the additional assumption that the permanent innovations η_t are uncorrelated with the remaining elements $\tilde{\eta}_t$ of the transformed innovations vector.[5]

Summarizing, the common trends model (3.3) has three desirable features. First, the model itself imposes no overidentifying restrictions beyond the testable restrictions imposed by cointegration, although additional assumptions are necessary to examine dynamic features of the model. Second, it permits rather general correlations between specific permanent and transitory shocks. Third, as is described below, the model is easily estimated using a modified version of a VAR, a vector error correction model (VECM).

Estimation Strategy

The estimation of the common trends model consists of three parts, each employing the additonal identification restrictions discussed above.

1. *Test for cointegration.* Stock-Watson (1986) tests are performed for the order of cointegration (or, equivalently, for the number of common trends) in X_t. The tests entail examining the real part of the k'-th root of the first order autoregressive matrix of X_t under the null hypothesis that this matrix has k roots equal to one and n-k roots with modulus (and therefore real parts) less than one, where $k'<k$. The cointegrating vectors of the system are also estimated and reported.[6]

2. *Estimate A, C(L).* The key to estimating C(L) in (3.3) is the one-to-one correspondence (derived in the Appendix) between the common trends model (3.1) and Engle and Granger's (1987) model of cointegrated processes. A popular procedure for estimating the moving average representation of a stationary multivariate time series model is to estimate a finite order VAR and then to invert the VAR. Granger's Representation Theorem (Engle and Granger [1987]) implies that a similar procedure can be used for cointegrated systems, except that the cointegrating conditions are imposed by estimating a VECM rather than a VAR. Specifically, it shows that all VECM models have a cointegrated representation of the form (3.3), and that all cointegrated models of the form (3.3) have a VECM representation (perhaps with a moving average error); that is, X_t have the representation,

$$\Delta X_t = a + B(L)\Delta X_{t-1} - d(\alpha' X_{t-1}) + \epsilon_t \tag{3.5}$$

where ϵ_t are the same innovations as in (3.3), a is $n\times1$, d is $n\times(n-k)$, B(L) is a $n\times n$ matrix lag polynomial, and where we assume that there is no moving average component to the error term. The n-k stationary variables $\alpha' X_t$ are called the "error-correction" terms. Thus C(L) and ϵ_t are computed by estimating (3.5), given α, for some specific lag order and inverting the resulting VECM. In our empirical implementations, the theoretical (rather than the estimated) cointegrating vectors are used to construct $\alpha' X_t$ in (3.5), making it possible to give the A matrix a simple interpretation.

The next step is the estimation of A. As discussed above, if k=1 then $\alpha' A=0$ identifies A up to scale. For k>1, suppose that A can be written as $A=A_0\Pi$, where A_0 is some n×k matrix satisfying $\alpha' A_0=0$, where A_0 is known (or depends only on the cointegrating vector) and Π is a lower triangular matrix of unknown parameters. (A motivation for this parameterization is provided in Section 5.) Then estimates of Π and A can be constructed from estimates of C(1) and $\Sigma=E(\epsilon_t \epsilon_t')$; in addition, as discussed in the Appendix, F can be computed from estimates of C(1) and Σ.[7] As discussed above, the long-run forecasts of X_t from the VECM (3.5) provide estimates of X_t^P, although it is simpler numerically to compute them as $A\tau_t$ after estimating A and τ_t.

3. *Compute innovations statistics.* Two measures of the relative importance of the permanent and transitory components are computed using the estimates of C(L) and ϵ_t and the additional identification restriction that η_t and $\tilde{\eta}_t$ are uncorrelated. This permits estimation of $F^\dagger$ and thus of $C^\dagger(L)$. Using these statistics, we calculate the implied changes in X_t brought about by one unit innovation in the trend component. This impulse response function shows the shape of the dynamic response of the variables to an innovation in the permanent component. Second, the relative importance of the response to a typical innovation in determining the short run evolution of variables is estimated by decomposing the variance of the k-step ahead forecast of each element of X_t into parts associated with the transitory and permanent innovations. This permits estimating the fraction of unforeseen movements in

X_t that can be attributed to innovations in the permanent component.

4. An Empirical Model of Consumption, Investment, and Income

We now turn to an empirical common trends model of the form (3.1) using output, consumption and investment, as suggested by the theoretical development of Section 2. The data, obtained from the Citibase data base, are quarterly from 1952:I through 1985:IV for the U.S. All variables are transformed by taking logarithms. The measures of output, consumption, and investment are the per capita values of GNP, personal consumption expenditures and gross private domestic investment from the National Income and Product Accounts, deflated by the GNP deflator.

Selected unit root and cointegration features of the data are investigated in Table 1, which presents tests of the null hypothesis that the series contains a stochastic trend (i.e. a unit root). For reference developing the mixed real/monetary model in the next section, the table also includes statistics for money, m (the logarithm of nominal M2 per capita) and price, p (the log of the GNP price deflator).[8]

The test statistics reported in Table 1 involve making various adjustments for the possible presence of time trends as an alternative to the unit roots hypothesis. In addition, both the Dickey-Fuller (1979) $\hat{\tau}$ statistics and the Stock-Watson (1986) q_f statistics involve an autoregressive approximation to the short run correlations in the series. The first column in panel A presents a test of the hypothesis that the series contain a unit root against the alternative that it is stationary, perhaps around a time trend of up to

Table 1

Univariate Series

Unit Root Statistics

A. Log Levels of Series

Series	$q_f^{\tau^2}(z)$	$q_f^{\tau}(\Delta z)$	$\hat{\tau}_\tau(\Delta z)$	$q_f^{\tau}(z)$	$\hat{\tau}_\tau(z)$	Time Trend in Δz
y	-13.1	-91.4**	-5.42**	-11.3	-2.53	0.44
c	-12.3	-116.1**	-4.76**	-12.7	-2.85	0.89
i	-29.1+	-111.5**	-6.37**	-28.7*	-4.17**	0.29
m	-7.1	-53.7**	-3.68*	-5.2	-2.89	2.61**
p	-2.7	-56.9**	-1.95	-4.2	-2.26	1.09

B. Error Correction Terms

Series	$q_f^{\tau}(z)$	$\hat{\tau}_\tau(z)$	Time Trend in z	$q_f^{\mu}(z)$	$\hat{\tau}_\mu(z)$
y - c	-15.1	-2.21	-0.64	-14.8*	-2.16
y - i	-34.1**	-4.62**	-1.66+	-31.0**	-4.29**
y + p - m	-15.9	-2.87	0.66	-15.2*	-2.87

Notes: Significant at the **1% *5% +10% level. All statistics are based on regressions with 4 lags. $q_f^{\tau^2}[z]$ denotes the Stock-Watson $q_f^{\tau^2}(1,0)$ statistic computed using the level of each variable; $q_f^{\tau}[\Delta z]$ denotes the $q_f^{\tau}(1,0)$ statistic computed using the first difference of each variable; $\hat{\tau}_\tau[\Delta z]$ denotes the Dickey-Fuller (1979) t-statistic computed using the first difference of x; and similarly for $q_f^{\tau}[z]$ and $\hat{\tau}_\tau[z]$. Critical values for the $\hat{\tau}_\tau$ statistic are from Fuller (1976, p. 373); for the $q_f^{\tau}(1,1)$ statistic are from Stock and Watson (1986a); and for the $q_f^{\tau^2}(k,k-1)$ statistics are from Appendix A of Stock and Watson (1987). The "time trend" entries denote the t-statistic on time in a regression of the variable on a constant, time, and four of its lags.

quadratic order. For all series, this test fails to reject the null at the 5% level, although the evidence of a unit root is weakest for investment. The second and third columns test for a second unit root against the alternative that the the process is stationary in differences, possibly with a time trend; the Stock-Watson tests reject the null for all series, while the Dickey-Fuller test rejects for all series except inflation. The final column presents the t-statistic on time in a regression of the first difference of each series on a constant time, and four of its lags. As found in Stock and Watson (1987) using monthly M1 data, money growth appears to be stationary around a time trend. Since the time trends on the other series are insignificant, the unit roots tests in the fourth and fifth columns are also reported; the unit root hypothesis is rejected by investment at the five but not the one percent level, while the other series fail to reject.

The economic model of Section 2 suggests that while consumption, income, and investment will contain unit roots, y-c and y-i will not. The stationarity of these "error correction" terms, along with log M2 velocity, is examined in panel B using the same procedures. There is strong evidence that y-i does not contain a unit root, although this result conflicts with the implications of panel A that y has a unit root but that i does not. The evidence that y-c and M2 velocity are stationary is weaker, resting on the 10% rejections based on the q_f^{μ} statistic (which tests against the alternative that the series is stationary with nonzero mean). Summarizing, we interpret these unit root tests as being broadly consistent with the hypothesis that there is one common trend among y, c and i, although the apparent inconsistencies in these results stress the importance of performing joint unit root tests on the trivariate system.[9]

A test of the hypothesis of three common trends (i.e. no cointegration) vs. the alternative of one common trend (i.e. two cointegrating vectors) is presented in Table 2. The test is based on the roots of the adjusted first order autocorrelation matrix Φ_f^τ defined in Stock and Watson (1986), computed using detrended data. The real parts of these estimated roots are .948, .858, and .810. The statistic tests the null hypothesis that the second of these roots is one, against the alternative that it has a real part that is less than one. The p-value of the corresponding $q_f^\tau(3,1)$ statistic is 11%, providing evidence against the hypothesis of three unit roots. The projection of the estimated cointegrating vectors on the theoretical cointegrating vectors of $(1,-1,0)'$ and $(1,0,-1)'$ indicates a reasonable correspondence to the theoretical predictions; a formal test of the equivalence of these estimated cointegrating vectors and the theoretical values would entail nonstandard distribution theory (see Stock [1984] and Sims, Stock and Watson [1986]), and we do not perform such a test here.

A VECM was estimated using four lags of the first difference of y, c and i, an intercept, and the two theoretical error correction terms y-c and y-i.[10] Since the theoretical model constrains A to be a 3×1 vector with equal elements, the permanent component has the same long run effect on each of the variables. The scale of the innovation to the trend is fixed by setting $A=(1\ 1\ 1)'$, so that a unit shock to the permanent component will eventually increase y, c and i by one.

The impulse responses of y_{t+k}, c_{t+k}, and i_{t+k} to a unit innovation in τ_t are plotted in Figure 1, along with their 90% confidence intervals.[11] The responses share a common "hump" shape. The point estimates suggest that an innovation which will eventually lead to a 1% increase in GNP results in a

Table 2
Common Trend Tests and Estimated Cointegrating Vectors

y, c, i

$$\begin{bmatrix} y \\ c \\ i \end{bmatrix} = \begin{bmatrix} 1.00 \\ 1.00 \\ 1.00 \end{bmatrix} \tau_{\tau} + D(L)\epsilon_t \,, \qquad \tau_t = \mu + \tau_{t-1} + \nu_t$$

Standard deviation (ν_t) = .80%

Common Trend test: $q_f^{\tau}(3,1) = -19.0$ p-value = .11

Estimated cointegrating vectors:

y	c	i
1.12	0.08	-0.83
0.90	-1.06	-0.13

Notes: The common trend tests are discussed in the text. The estimated cointegrating vectors have been rotated to provide a least squares fit to (1 -1 0) and (1 0 -1).

monotonic increase in y over the first year. This response peaks at approximately 1.3% and then oscillates while returning to its long run value of 1%. The response of consumption over the short horizon is more damped than the response of GNP. Interestingly, however, the consumption path fluctuates substantially in response to the permanent innovation, dipping to .8% at the three year horizon before returning to its 1% long-run value. The response of investment is much more dramatic than either income or consumption: a 1% permanent innovation leads to a 2.3% increase in investment after one year, followed by a decline to .4% at the three year horizon before slowly returning to its new permanent level. Thus innovations in the permanent component result in substantial transitory movements in all series -- particularly investment. The duration of these responses (one to four years) is consistent with "business cycle" horizons. However, the wide 90% confidence intervals caution against interpreting the point estimates too closely.

Are these responses large enough to explain a substantial fraction of the short run variation in the data? This question is addressed in Table 3, which presents the variance decompositions of the data for various forecast horizons. The table shows the fraction of the variance of the forecast error in the series that is attributable to innovations in the permanent component at various forecast horizons. These innovations play an important role in the variation in GNP and consumption. At the 1-4 quarter horizon, the point estimates suggest that 30% to 50% of the fluctuations in GNP can be attributed to the permanent component. This increases to 70% at the two year horizon and to 80% at four years. The importance of the permanent component to consumption is even greater.[12] Interestingly, the permanent component explains a much smaller fraction of the movements in investment -- less than

Figure 1a. Response of y to an innovation in the permanent component

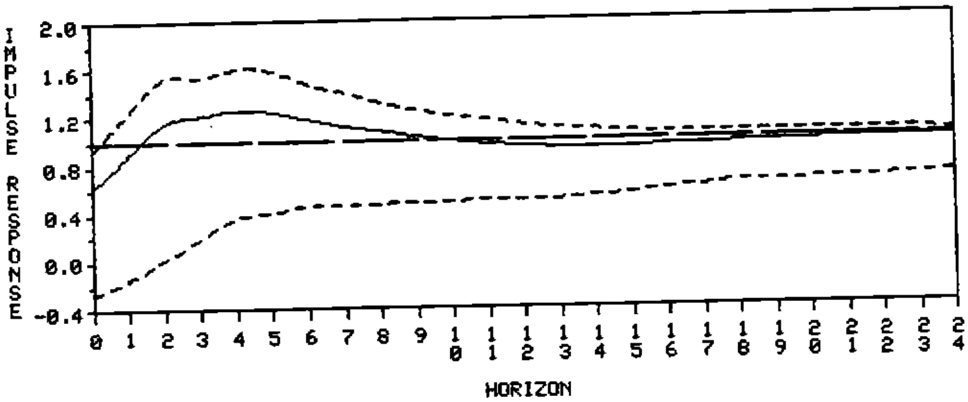


Figure 1b. Response of c to an innovation in the permanent component

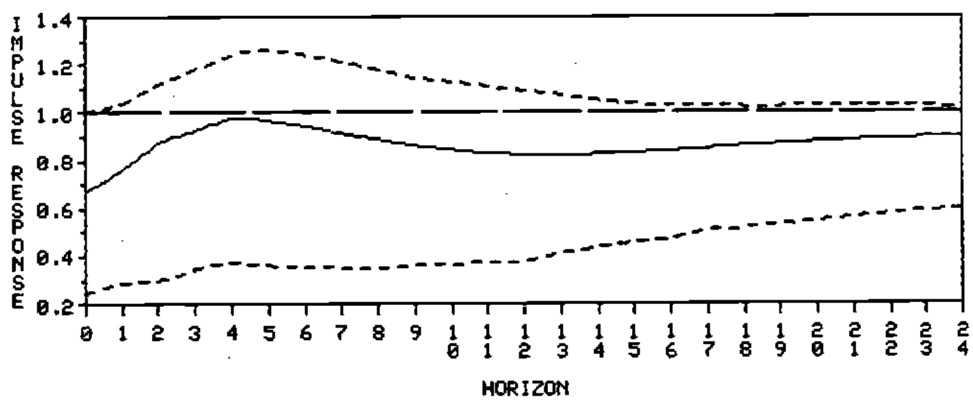


Figure 1c. Response of i to an innovation in the permanent component

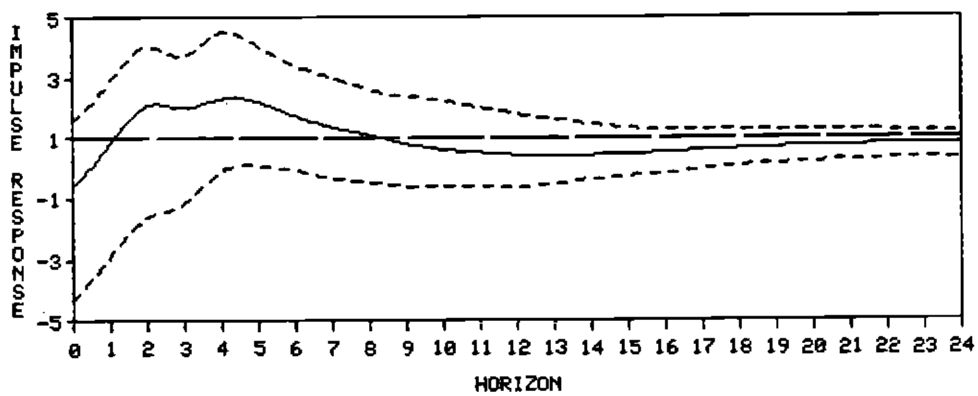


Figure 1

Impulse responses to a unit innovation in the permanent component, three variable common trends model

——— Impulse response

\- - - - 90% confidence band

Table 3

Fraction of Variance Attributed to Innovation in Permanent Component -- Real Model

Variables: y, c, i

Horizon	Series: y	c	i
1	0.304 (.002 .703)	0.637 (.141 .870)	0.012 (.001 .477)
4	0.516 (.030 .807)	0.734 (.234 .882)	0.073 (.029 .356)
8	0.688 (.155 .847)	0.780 (.298 .910)	0.152 (.051 .408)
12	0.752 (.272 .865)	0.783 (.342 .930)	0.155 (.056 .422)
16	0.789 (.369 .883)	0.796 (.399 .942)	0.155 (.059 .435)
20	0.818 (.440 .901)	0.817 (.468 .952)	0.161 (.065 .441)
∞	1.00	1.00	1.00

Notes: 90% confidence intervals are given in parentheses. The confidence intervals were computed using 500 bootstrap replications based on the estimated VECM(4) representation of the Common Trends model. The bootstrapped estimates were obtained using the procedure described by Runkle (1987).

20% at horizons up to five years.[13]

5. A Mixed Real-Monetary Empirical Model

In this section we extend our analysis to include money and prices, so that shocks to money and prices can play a role in our empirical explanation of economic fluctuations. The unit roots tests reported in Tables 1 and 2 are generally consistent with the hypothesis that the three-variable system contains one common trend; to the extent that the results of Table 1 suggest that velocity is stationary, the five-variable system should contain three cointegrating vectors and two common trends. The roots of the adjusted first order autocorrelation matrix described in the preceding section are qualitatively consistent with this conjecture, with real parts of .958, .958, .869, .869, and .851. However, the $q_f^{\tau^2}(5,3)$ statistic (which allows for a possible quadratic trend, necessary because of the evident time trend in money growth), based on the third smallest of these real parts, has a p-value of .54. While the various tests, taken literally, yield mixed information about the number of unit roots in the five variable system, a possible resolution of the conflicting results comes from recognizing that the power of the multivariate unit root tests can be substantially less than the power of the corresponding univariate tests, particularly when the series have been linearly or quadratically detrended. Indeed, since the 5% critical value of the $q_f^{\tau^2}(5,3)$ is approximately -27.9, more than fifty years of quarterly data would be necessary to reject the hypothesis at the 5% level using the observed value of the third largest root, .869.[14] Although the evidence is mixed, we conclude that the five-variable system contains two common trends.

Since the five variable system contains two common trends, there are three linearly independent cointegrating vectors. Including the cointegrating vector defined by M2 velocity and ordering the variables as (y,c,i,m,p), these are (1,-1,0,0,0)', (1,0,-1,0,0)', and (1,0,0,-1,1)'. The estimated cointegrating vectors based on the quadratically detrended data are reported in Table 4. These point estimates are generally consistent with the theoretical values of that were used in the estimation of the VECM.

Because this model has more than one common trend, additional identifying assumptions must be made to estimate A and τ_t. We adopt a specification in which the trends have a natural interpretation and have uncorrelated innovations. The preceding discussion suggests that the five-variable model will inherit one stochastic trend common to the real variables. This will be augmented by a "nominal" stochastic trend relating the long-run movements of money and prices. There are two obvious parameterizations with this characteristic. Both involve one "real" and one "nominal" trend, in the sense that the long run effect on the real variables of a unit impulse to the real permanent component is normalized to be one, while the long run effect on the nominal variables of a unit impulse in the nominal component is similarly set to one. In both parameterizations, the innovations in the nominal and real components are uncorrelated by assumption.

In the first parameterization, the long run effect on the price level of an innovation to the real permanent component is constrained to be zero. In contrast, an innovation in the nominal component is permitted to have a possibly nonzero long run effect π on output. Thus:

$$(5.1) \qquad X_t = \gamma + \begin{bmatrix} \pi & 1 \\ \pi & 1 \\ \pi & 1 \\ 1+\pi & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \tau_{1t} \\ \tau_{2t} \end{bmatrix} + D(L)\epsilon_t \quad .$$

If π is zero, then only τ_{2t} (the real permanent component) has a long run effect on the real variables. To maintain the velocity cointegration relation, if $\pi=0$ in (5.1) a unit increase in the real permanent component corresponds to a long run increase in output and money by one percent, with prices remaining unchanged by assumption. If π is nonzero, the permanent effect of a unit increase in the nominal component is a long run rise of the real variables by π%.

An alternative parameterization would reverse the zero restriction in (5.1): the nominal component is normalized to have no permanent effect on the real variables, while the real component is permitted to have a permanent effect on the price level. Accordingly,

$$(5.2) \qquad X_t = \gamma + \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 1+\rho & 1 \\ \rho & 1 \end{bmatrix} \begin{bmatrix} \tau_{1t} \\ \tau_{2t} \end{bmatrix} + D(L)\epsilon_t$$

where ρ is an unknown parameter. In (5.2), τ_{1t} is the real component, while τ_{2t} is the nominal component. Here, the long run effect of a unit increase in the real component is to increase prices by ρ%.

The representations (5.1) and (5.2) are identical if the correlations in Δx_t^p are such that $\pi=0$ (or equivalently $\rho=0$). For our data this is very nearly the case, so that the interpretations that follows from the two normalizations are essentially identical. Henceforth the estimation and discussion will be based solely on the formulation (5.1).

The model (5.1) was estimated using a VECM(4) with y-c, y-i, and v as the "error correction" terms. Noting that A can be written as $A=A_0\Pi$, where A_0 is a 5×2 matrix of constants (given the cointegrating vectors) and where the 2×2 matrix Π is lower triangular with ones on the diagonal and with $\Pi_{21}=\pi$ unknown, the algorithm discussed in Section 3 was used to estimate π and thus A.[15] Some summary statistics for the estimated model are shown in Table 4. The estimated value of A implies that an innovation leading to a long-run increase in prices by 1% leads a long-run reduction in y, c, and i by .01%. However, this effect is estimated imprecisely, with a 90% (bootstrapped) confidence interval ranging from -.74% to +.25%.[16]

The estimated impulse response functions for this model are presented in Figure 2. The point estimates suggest that an innovation in the nominal permanent component is initially associated with a sharp growth of M2, a slower growth of prices, and a jump in investment activity. After several quarters, money supply growth remains positive but slows, prices continue to rise, and investment drops, fluctuating around zero as it returns to its long run value. Although the nominal permanent innovation has a modest transient effect on GNP, peaking at the two to three quarter horizon, the effect on consumption is slight at all horizons.

The estimated responses of GNP and consumption to the innovation in the second, "real" permanent component are broadly similar to those reported for

Table 4

Common Trend Tests and Estimated Cointegrating Vectors -- Mixed Real-Monetary Model

y, c, i, m, p

$$\begin{bmatrix} y \\ c \\ i \\ m \\ p \end{bmatrix} = \begin{bmatrix} \pi & 1.00 \\ \pi & 1.00 \\ \pi & 1.00 \\ 1+\pi & 1.00 \\ 1.00 & 0 \end{bmatrix} \tau_t + D(L)\epsilon_t \quad , \quad \tau_t = \mu + \tau_{t-1} + \eta_t$$

$\hat{\pi}$ = -0.01 [90% Confidence Interval (-.74,.25)]
Standard deviation (η_{1t}) = 2.01%
Standard deviation (η_{2t}) = 0.81%

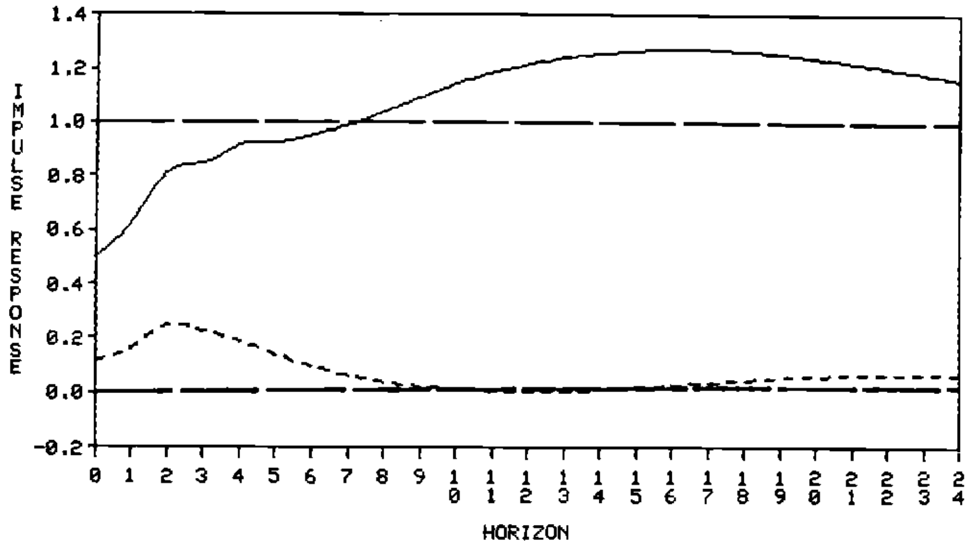
Common Trend test: $q_f^{\tau^2}(5,2) = -17.9$ p-value = .54

Estimated cointegrating vectors:

y	c	i	m	p
0.98	-0.01	-1.01	0.01	0.05
0.98	-1.01	-0.01	0.01	0.04
1.10	0.08	0.08	-1.08	0.72

Notes: The common trend tests are discussed in the text. The estimated cointegrating vectors have been rotated to provide a least squares fit to (1 -1 0 0 0), (1 0 -1 0 0) and (1 0 0 -1 1). $\hat{\pi}$ was estimated using a VECM(4) as discussed in the text.

Figure 2a. Response of y



- - - - Response to first (nominal) permanent innovation
——— Response to second (real) permanent innovation

Figure 2b. Response of c

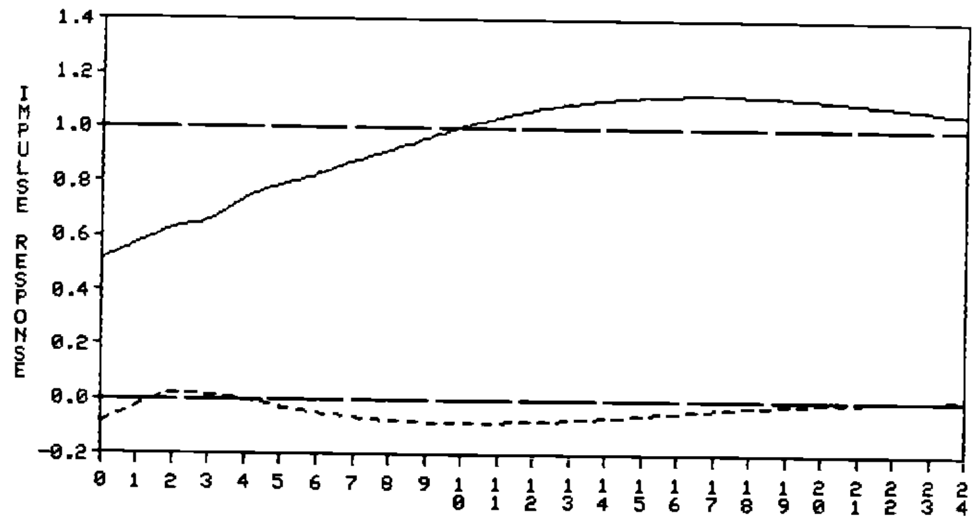


Figure 2c. Response of i

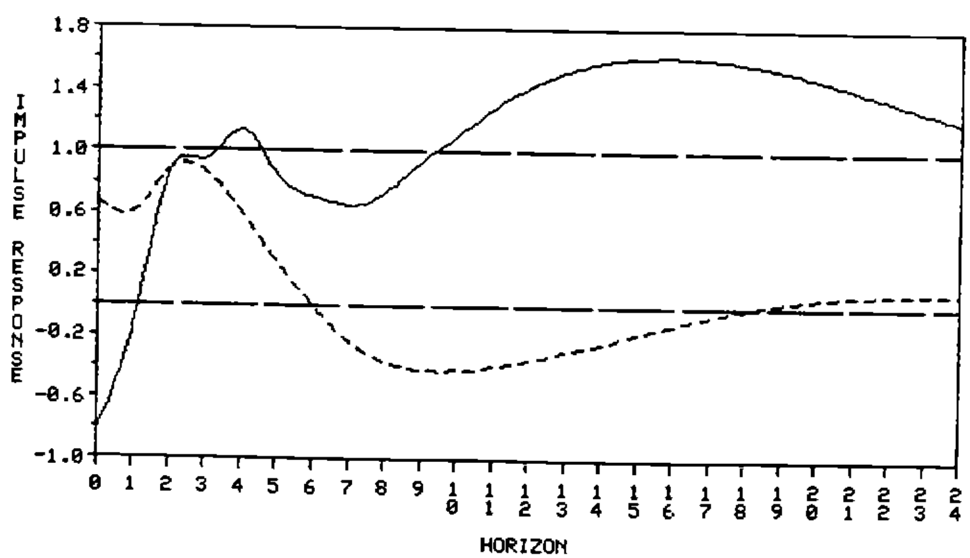


Figure 2d. Response of m

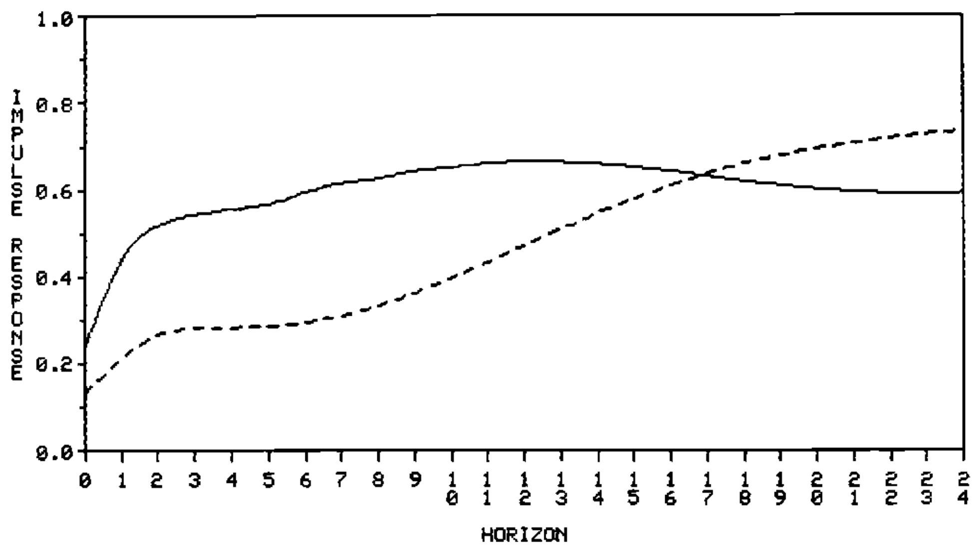


Figure 2e. Response of p

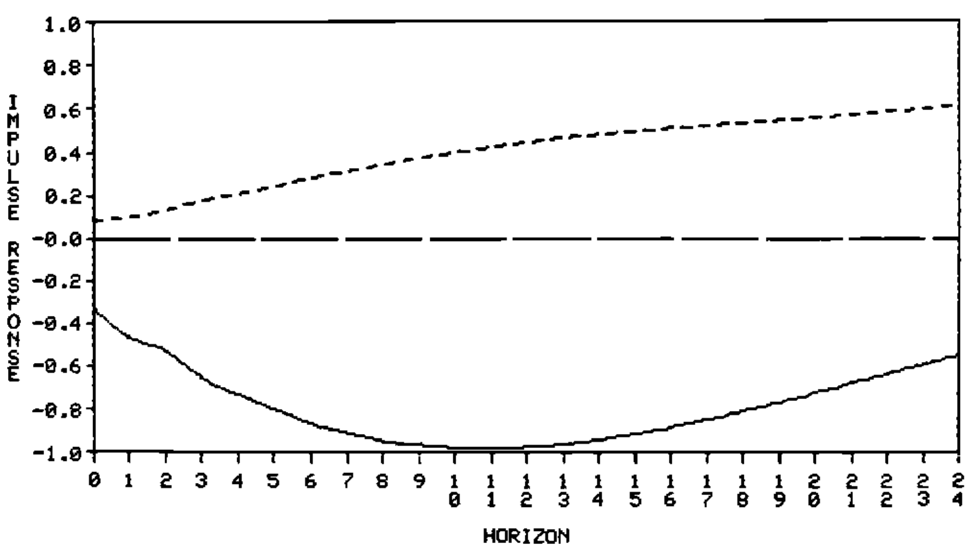


Figure 2
Impulse responses to a unit innovation in the permanent components, five variable common trends model

- - - - Response to first (nominal) permanent innovation
——— Response to second (real) permanent innovation

Table 5a

Fraction of Variance Attributed to Innovation
in First (Nominal) Permanent Component -- Mixed Real-Monetary Model

Horizon	y	c	i	m	p
1	0.083 (.000 .357)	0.111 (.007 .474)	0.123 (.001 .391)	0.312 (.007 .532)	0.228 (.026 .824)
4	0.210 (.010 .416)	0.034 (.018 .392)	0.214 (.019 .427)	0.349 (.010 .598)	0.240 (.036 .868)
8	0.141 (.023 .366)	0.026 (.021 .482)	0.167 (.038 .367)	0.369 (.013 .624)	0.324 (.069 .908)
12	0.088 (.038 .432)	0.038 (.019 .596)	0.163 (.045 .417)	0.467 (.024 .686)	0.407 (.138 .933)
16	0.062 (.040 .539)	0.038 (.017 .642)	0.162 (.051 .432)	0.584 (.041 .760)	0.483 (.219 .949)
20	0.049 (.038 .567)	0.032 (.020 .652)	0.153 (.055 .435)	0.674 (.063 .821)	0.550 (.309 .959)
∞	0.000	0.000	0.000	0.863	1.00

Notes: See the notes to Table 3.

the corresponding trivariate model in Section 4, although the responses are typically slower in the five variable case. GNP exhibits a similar "hump-shaped" response, peaking after four years. Investment exhibits a strong oscillatory pattern with an initial negative response. The initial response of prices to the real innovation is a sharp deflation, becoming inflationary only after three years. Interestingly, the initial response of real balances to the real innovation is to increase sharply: despite the growth in GNP, with prices falling and nominal money expanding, velocity drops by .5% after six quarters, and is still off by .3% after four years.[17]

The forecast error variance decompositions (reported in Table 5) are generally consistent with the impulse response functions and, where they overlap, with the results for the trivariate model of Section 4. The results in Table 5 suggest that the real permanent innovation plays a dominant role in fluctuations in y and c at forecast horizons of eight quarters or more. In contrast, only a small fraction of the variation in investment is explained by this factor even over horizons as long as 5 years. Innovations in the real component also play an important role in explaining fluctuations in m and p, even at short horizons. While the nominal component accounts for a negligible proportion of the variation in c, it explains 20% of the variability in y and i at the one year horizon. The two factors are roughly equally important in explaining price movements at business cycle horizons, although the nominal factor plays the more important role in monetary fluctuations.[18]

As a measure of the historical importance of the response of GNP to the real trend, the eight quarter ahead forecast error for GNP is plotted in Figure 3, along with that part of this forecast error attributable to errors in forecasting the real permanent component. As discussed by Blanchard and

Table 5b

Fraction of Variance Attributed to Innovation
in Second (Real) Permanent Component -- Mixed Real-Monetary Model

Horizon	y	c	i	m	p
1	0.262 (.008 .587)	0.453 (.038 .714)	0.021 (.001 .258)	0.155 (.043 .716)	0.436 (.002 .537)
4	0.443 (.147 .742)	0.664 (.236 .826)	0.032 (.019 .283)	0.205 (.080 .744)	0.454 (.005 .585)
8	0.562 (.267 .715)	0.697 (.228 .801)	0.045 (.027 .300)	0.221 (.102 .730)	0.428 (.004 .571)
12	0.652 (.266 .735)	0.742 (.211 .825)	0.061 (.034 .289)	0.244 (.118 .742)	0.391 (.003 .542)
16	0.730 (.245 .769)	0.799 (.214 .856)	0.110 (.053 .318)	0.228 (.107 .764)	0.352 (.003 .515)
20	0.784 (.249 .810)	0.843 (.233 .872)	0.158 (.068 .347)	0.196 (.091 .765)	0.311 (.003 .468)
∞	1.000	1.000	1.000	0.137	0.00

Notes: See the notes to Table 3.

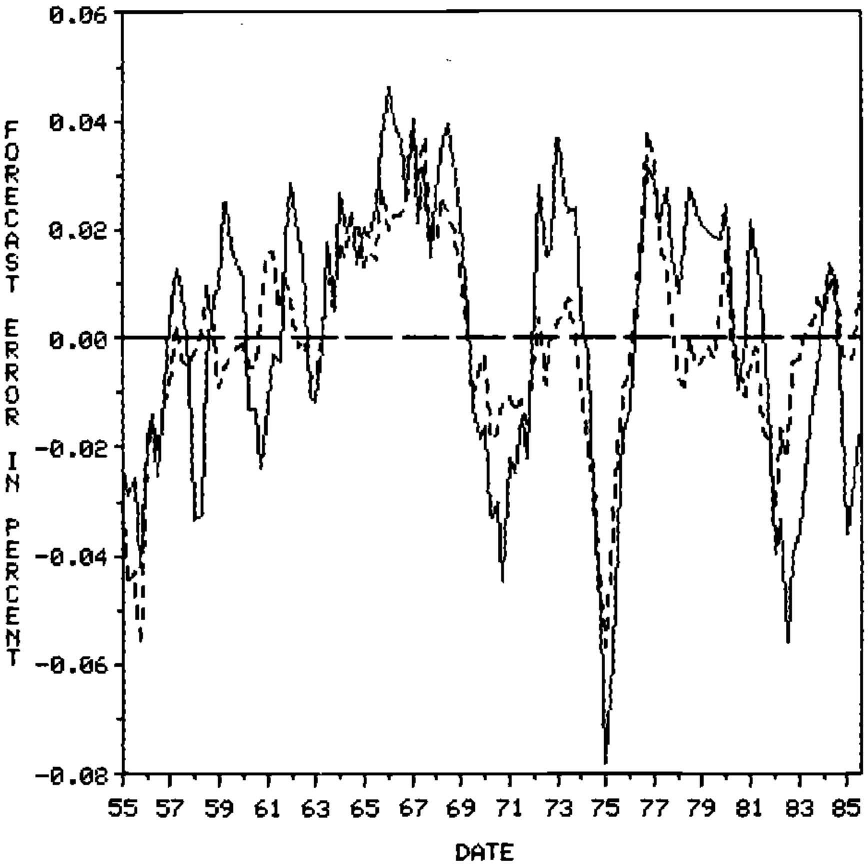


Figure 3
Historical decomposition of GNP Forecast Error, Eight Quarters Ahead
Based on the five variable common trends model

——— Total GNP forecast error
- - - - Forecast error attributable to the real permanent factor

Watson (1986), the former series closely resembles the popular notion of the postwar U.S. "business cycle," with turning points coinciding with NBER-dated cyclical peaks and troughs. The error attributed to the real permanent component tracks the total forecast error rather closely. In particular, the real permanent component appears to have played an important role in the expansion of the 1960's, in the 1975 recession, and in the short recession of early 1980. In contrast, this series explains little of the movement in 1957-58 and in the more prolonged 1982 downturn.

The interpretation of τ_t in the first model as a permanent shock requires that the innovations ϵ_t span the space of underlying structural disturbances. If there are a large number of structural disturbances generating X_t, then it is possible that the estimated permanent innovation is capturing the effects of a complicated function of these disturbances. Thus if our findings from Section 4 were spuriously caused by the limited information set, we would expect to find substantially different results when the information set is increased. Specifically, if the model of Section 4 is a perfect characterization of the relationship between y, c and i, then its permanent component and the second permanent component in Model 2 should be the same. In fact, the two components are similar, having a correlation of .86.

6. Analysis of Trend and Stationary Components of GNP

The expression (3.5) provides a decomposition of X_t into a permanent (or trend) and a stationary (or "cyclical") component. These permanent and cyclical components of GNP, and the innovations η_t in the underlying stochastic trends from the five-variable model, are now briefly compared with some alternative measures of productivity, trend GNP, and cyclical fluctuations.

The trend component of GNP, y_t^p, is plotted in Figure 4, along with Denison's (1985) estimate of real potential GNP per capita.[19] Despite the different approaches used to construct the two trend estimates, they are broadly similar. The three major differences between the two series are the treatments of the prolonged growth of the 1960's (where the Common Trends model ascribes more of this growth to a shift in the trend), the 1974 contraction (where again the Common Trends model attributes much of the decline to a shift in trend GNP), and the slowdown of the late 1970's (in which Denison's potential GNP is consistently higher than the trend GNP (y_t^s) from the Common Trends model). In addition, the stationary component of GNP and the unemployment rate are plotted in Figure 5. The correlation between the stationary component and linearly detrended unemployment is -.53.

We interpret these broad similarities as checks that our techniques provide an estimate of "trend" and "cyclical" GNP that is consistent with what other researchers, from very different perspectives, take to be "reasonable" estimates. This is not to suggest that these methods should be used to detrend economic time series for use in subsequent econometric modeling. Indeed, a central point of this paper is to show the importance of innovations in trend components in explaining shorter run "business cycle" fluctuations. Stated another way, our results suggest that techniques that arbitrarily separate high and low frequency components of macroeconomic data will miss important linkages between the two, thereby resulting in misleading inferences.

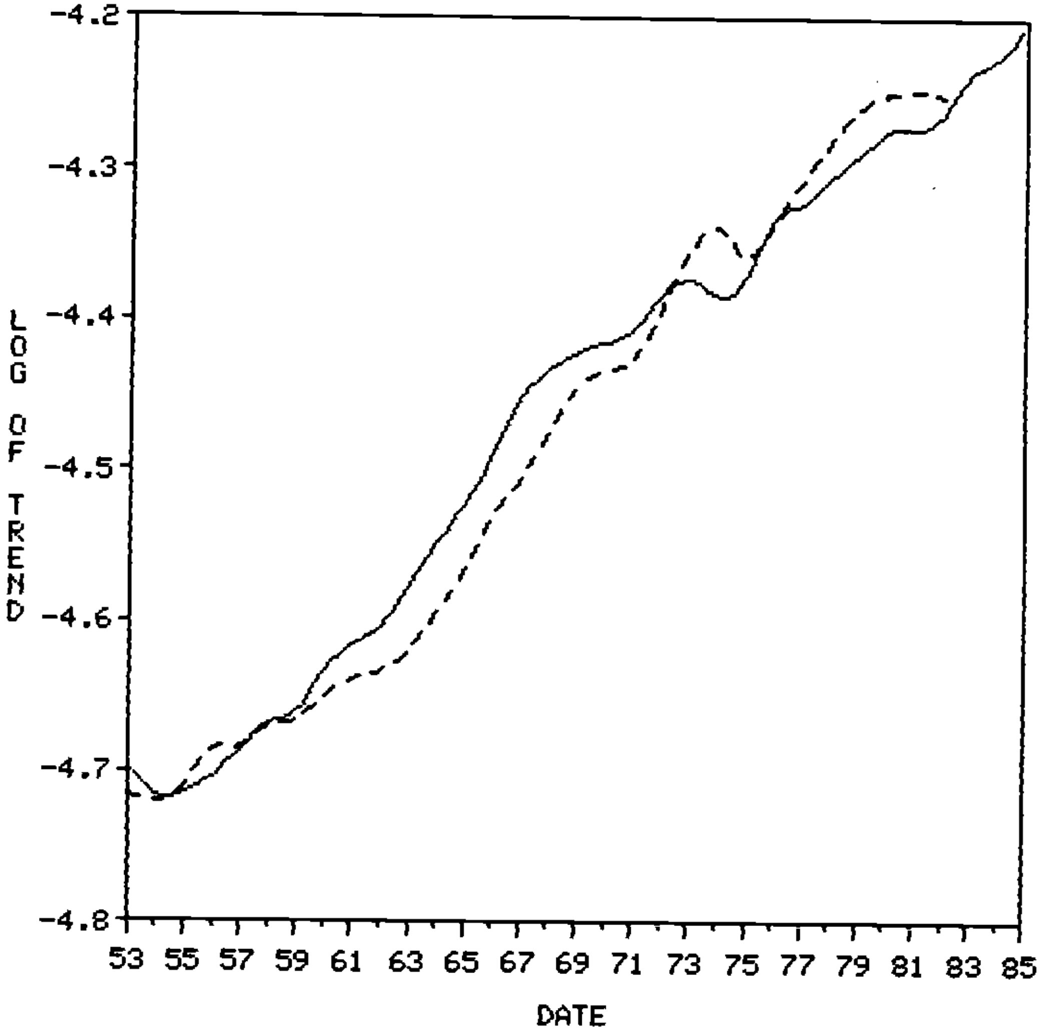


Figure 4
Estimates of Annual Trend GNP

- - - - Denison (1985, Table 2-2)
——— Permanent component of GNP from the five variable common trends model described in the text.

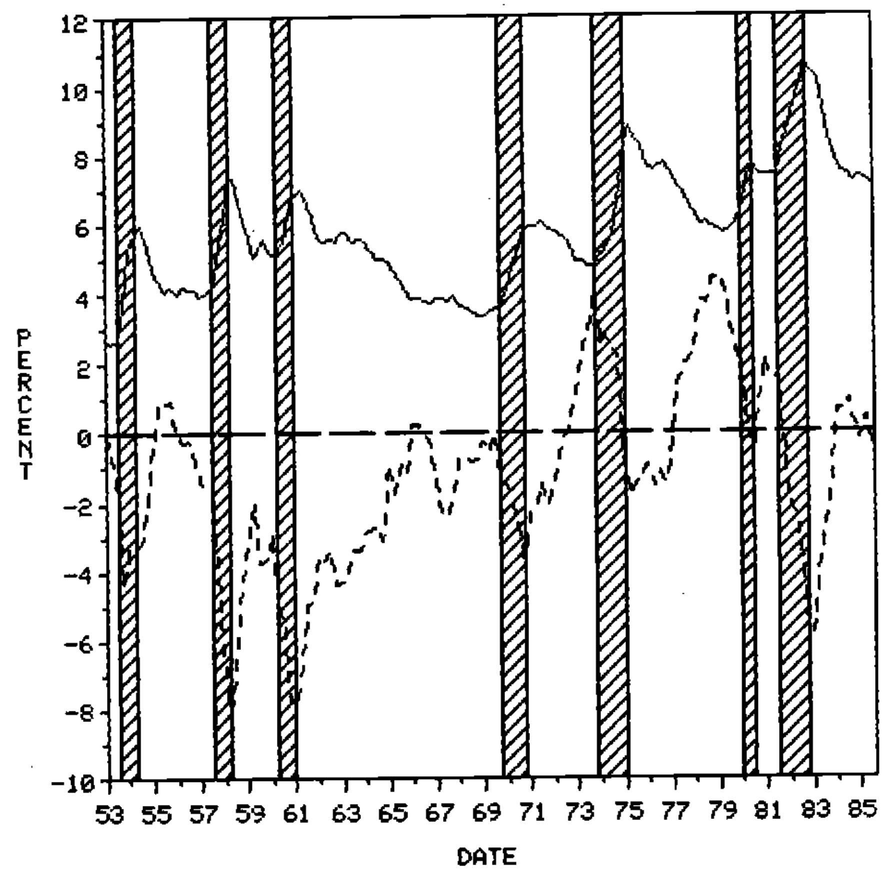


Figure 5
Quarterly unemployment and the Stationary Component of GNP

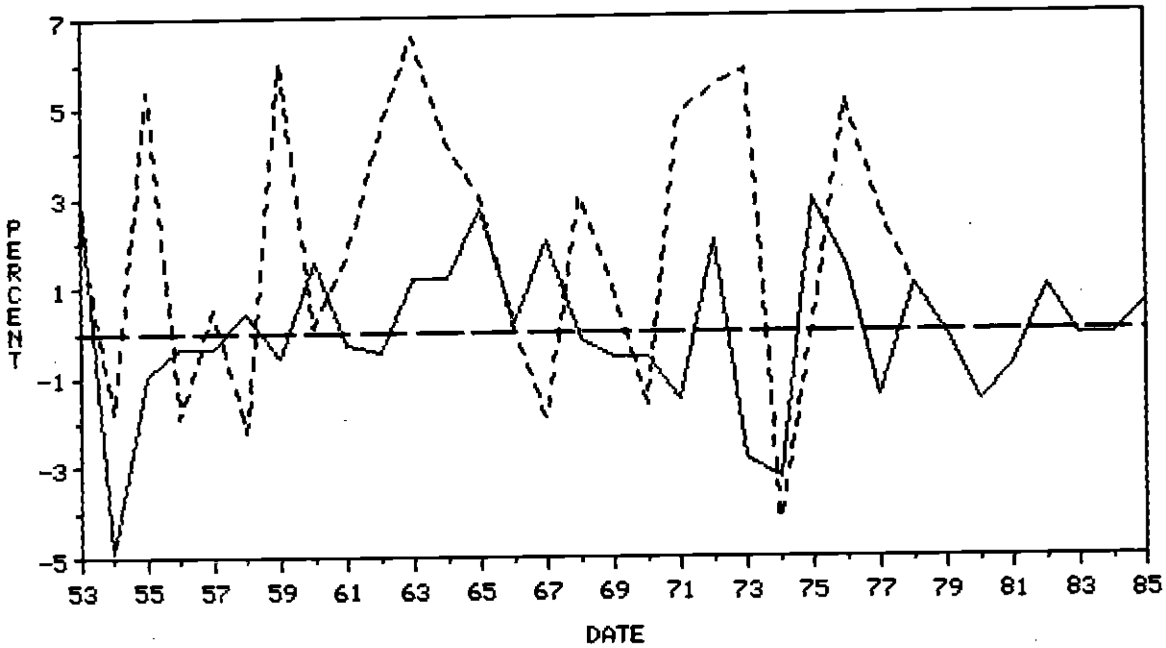
——— Unemployment rate
- - - - Stationary component of GNP from the five variable common trends model described in the text.

In the theoretical model of Section 2, the long run movements in aggregate variables arise from changes in productivity. Is there any evidence that productivity movements are related to innovations in the trend component of GNP or, more generally, to η_t? We investigate this by comparing these estimated innovations to a popular measure of the change in total factor productivity in the economy, the Solow (1957) residual. If the economy can be characterized by a Cobb-Douglas production function -- as in the theoretical model of Section 2 -- the Solow residual has the convenient interpretation of being exactly $\Delta\log(\lambda_t)$ in (2.2).[20] We use two measures of this productivity residual, Hall's (1986, Table 1) estimate for total manufacturing and Prescott's (1986) economy-wide estimate based on Hansen's (1984) adjusted hours series.[21] Hall's series is reported annually, and we have aggregated Prescott's quarterly series to the annual level for comparability.

The time path of the Solow residual and the change in the permanent component of GNP from the five variable Common Trend model is plotted in Figure 6a for Hall's measure and in Figure 6b for Prescott's measure. Visual examination suggests that the relationship between the Solow residual and $\Delta\tau_{2t}$ was stronger in the 1970's than it was in the 1950's and 1960's. In addition, Hall's productivity measure was substantially more volatile than the innovation in the trend component of GNP in the early period. Overall, the correlation of the innovation in the real factor with Hall's measure is very low, .12, and the correlation with Prescott's measure is only .42. Of course, the Solow residual is an imperfect measure of technical change; for example, Prescott (1986) points to errors in measuring the variables used in its construction, and Hall (1986) has suggested that this measure of productivity will misrepresent true technological progress in noncompetitive environments

Figure 6a

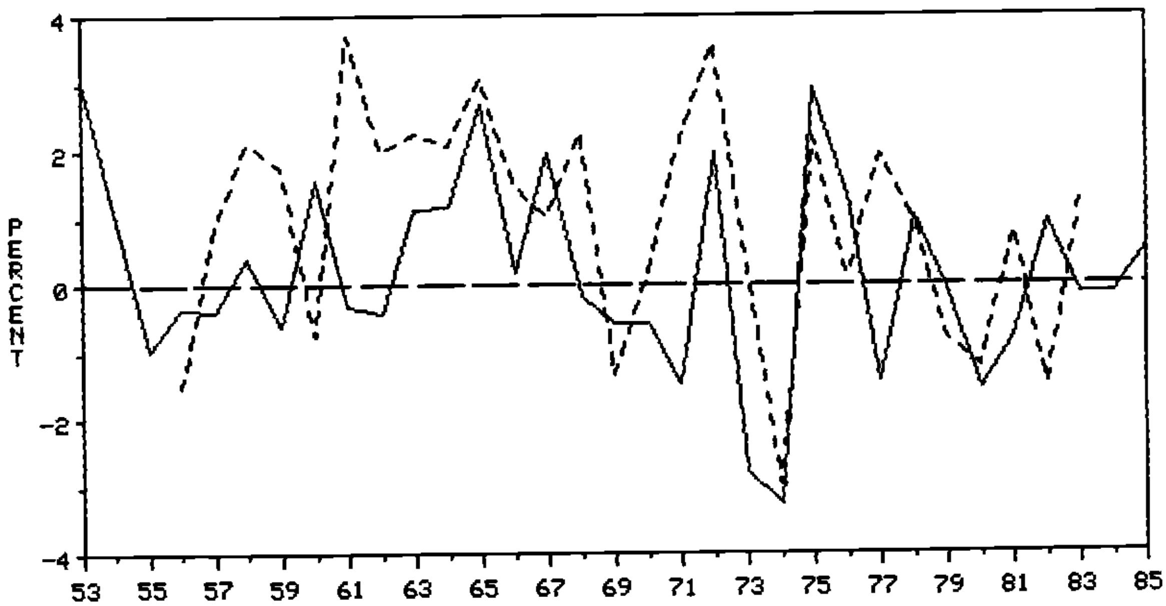
Hall's Estimate of Solow Residual



- - - - Solow residual (Hall [1986, Table 1])
——— Innovation to real permanent component from the five variable common trends model described in the text.

Figure 6b

PRESCOTT'S ESTIMATE OF SOLOW RESIDUAL



- - - - Solow residual (Prescott [1986])
——— Innovation to real permanent component from the five variable common trends model described in the text.

Figure 6.
Innovations in the real permanent component and annual estimates of the Solow productivity residual.

where price exceeds marginal cost. Nonetheless, these results suggest that large parts of the movement in the permanent components and in the change in trend GNP are not accounted for by changes in productivity, particularly in the early part of the sample, at least as measured by Prescott's and Hall's series.

7. Conclusions

The results in this paper suggest that there is an important empirical relationship in aggregate U.S. data between long run growth and movements over the one to four year horizon, where "long run" movements are formally identified by modeling them as random walks with drifts. In particular, the series we examine are well characterized as having a reduced number of common stochastic trends, and innovations in these permanent trends seem to be closely related to temporary economic fluctuations. These results emphasize that it is important to study the permanent and transitory components of macroeconomic time series simultaneously, and that analyzing the residuals obtained after extracting a trend -- stochastic or otherwise -- is likely to be misleading.

Focusing on real per capita GNP, the more important of the permanent components in our five-variable system is a stochastic trend that we associate with a shock to the real economy; this component accounted for over one-half the forecast error variance in GNP at the two year horizon. In contrast, a permanent nominal shock is of substantially less overall importance in the evolution of GNP. However, a qualitative examination of the 8-quarter ahead forecast errors indicates that there are important features of the history of GNP not explained by movements in the real component, in particular the fluctuations of the late 1950's and the 1981-2 recession. While it is tempting to identify the permanent shock to the real economy as an innovation in productivity, our estimate of this shock is only weakly correlated with two recent measures of Solow's (1957) productivity residual.

Footnotes

1. Using a closely related model, Christiano (1987) obtained simulation results indicating this positive short-run response of hours to an unanticipated productivity improvement.

2. Extensions to incorporate monetary systems of various sorts have been undertaken by King and Plosser (1984) and Eichenbaum and Singleton (1986). The former paper utilizes a conventional macroeconomic approach, so that the dynamics of real quantities are not influenced by incorporation of banking and currency. In particular, the King-Plosser economy is one in which the substitution effects of sustained inflation are taken to be small for real quantities with the exception of currency and bank deposits. The latter paper uses a general equilibrium, cash-in-advance framework which places greater stress on the allocative role of banking and currency, thereby highlighting the substitution effect of sustained inflation as higher inflation induces alterations in the real dynamics of quantities.

3. The estimates are optimal in the sense that they are the linear minimum mean square estimates formed from current and lagged values of X_t.

4. Both of these approaches would require the complicated nonlinear estimation techniques associated with dynamic factor models or multivariate unobserved components models, as discussed by Geweke and Singleton (1981), Watson and Engle (1983), or Harvey (1985).

5. Additional assumption concerning the ordering of $\tilde{\eta}_t$ would be necessary to compute impulse responses and variance decompositions with respect to these remaining elements of $\eta_t^{\dagger}$, although we do not perform such calculations.

6. There are a variety of ways to estimate the cointegrating vectors; Stock (1984) shows that the OLS estimator based on regressions with contemporaneous variables are consistent, and Stock and Watson (1986) use principal components to estimate the cointegrating vectors. Here we use the estimated eigenvectors corresponding to the smallest n-k roots of the first order autocorrelation matrix obtained by regressing X_t against its lag, after detrending the data with t^j, $j=0,1,2$ (the rationale for the quadratic detrending is given below). When a pair of complex eigenvectors (α_1,α_2) were computed, the cointegrating vectors were taken be to the real linear combinations, $\alpha_1+\alpha_2$ and $i\alpha_1-i\alpha_2$, where $i=\sqrt{-1}$.

7. From (3.1), (3.2) and (3.3) it follows that, conditional on $\epsilon_s=0$ for $s\leq0$, $X_t^p=C(1)\sum_{s=1}^{t}\epsilon_s=A\tau_t$. Combining this with the assumption that $E\eta_t\eta_t'=I_k$ (the k×k identity matrix), it follows that $C(1)\Sigma C(1)'=A_0\Pi\Pi'A_0$. Given estimates of Σ and $C(1)$, Π therefore can be estimated as the Cholesky factor of $(A_0'A_0)^{-1}A_0'C(1)\Sigma C(1)'A_0(A_0'A_0)^{-1}$. F can be estimated from the

eigenvectors corresponding to the nonzero eigenvalues of C(1), although in practice it is sometimes easier to use the corresponding eigenvectors of the symmetric matrix $C(1)C(1)'$.

8. The Citibase M2 series was used for 1959:1-1985:4; the earlier M2 data was formed by splicing the M2 series reported in <u>Banking and Monetary Statistics, 1941-1970</u>, Board of Governors of the Federal Reserve System to the Citibase data in January 1959. We thank Dennis Kraft for his advice in this matter. The monthly data were averaged to obtain the the quarterly observations.

9. For comparable univariate results obtained using the Phillips-Perron (1986) test statistic, see Perron (1986).

10. The estimation period was 1953:I to 1985:IV, using the 1952 observations for initial conditions.

11. Since the permanent component has a positive drift, the reported impulse responses are actually deviations from a (common) deterministic time trend. Thus a permanent response of 1% actually represents a shift upwards of the long-run growth path by 1%. The confidence intervals for the impulse response functions and variance decompositions were computed using 500 bootstrap replications. The procedure is that described for VAR's in Runkle (1987), except that the basis of the bootstrap was the VECM described in Section 3.

12. This should not be a surprising result. If consumption followed a random walk with drift, then our model implies that consumption and τ_t are identical.

13. The point estimates measuring the importance to GNP of the permanent component drop somewhat when the lag length is increased from 4 to 6 (although they are within the 90% confidence intervals in Table 3), while remaining roughly unchanged for consumption and investment. For example, at the 8 quarter horizon the permanent component explains 41%, 78% and 20% of y, c and i, respectively. This measure drops further (for y) when the number of lags is increased from 6 to 8. However, conventional tests suggest that 4 lags are adequate, relative to either 6 or 8. For example, the likelihood ratio test for four lags vs. 8 lags (calculated using the degrees of freedom correction suggested by Sims [1980]) has a p-value of .36. The F-Statistics for the individual equations have p-values .59 (GNP), .81 (Consumption), and .32 (Investment).

14. For additional discussion of the power of these tests, see Stock and Watson (1986, section 7).

15. Specifically, $A_0=[A_{01}\ A_{02}]$, where $A_{01}=(0\ 0\ 0\ 1\ 1)'$ and $A_{02}=(1\ 1\ 1\ 1\ 0)'$. Note that (5.2) also can be written in this form, with $A_0=[A_{02}\ A_{01}]$, where A_{01} and A_{02} are as defined for (5.1).

16. From the expression in footnote 7, Π can be estimated nonparametrically as the Cholesky factor of $(A_0'A_0)^{-1}A_0'(2\pi\hat{S}_{\Delta X}(0))A_0(A_0'A_0)^{-1}$, where $\hat{S}_{\Delta X}(0)$ is an estimate the spectral density matrix of ΔX_t at frequency zero. The estimate in Table 4 is based on a fourth order VECM approximation to this spectral density. As an alternative, when $\hat{S}_{\Delta X}(0)$ is estimated using a

Bartlett (triangular) window with a truncation point of four autocovariances, $\hat{\pi}=-.04$; with a truncation point of 10, $\hat{\pi}=.18$. In addition, the mean and the median of the bootstrapped confidence intervals is less than -.01, suggesting that the reported estimate in Table 4 is biased downwards. These results reinforce the conclusion that π is small, but is estimated imprecisely.

17. Confidence intervals for these impulse responses were also calculated, although they are not reported since they complicate the figures substantially. Broadly speaking, the confidence intervals for this model are similar to those calculated for the 3 variable model, indicating rather imprecise the point estimates.

18. Using a VECM(6), the 8-quarter ahead variance decompositions for (y,c,i,m,p) are: first component, (.20, .02, .25, .30, .32); second component, (.54, .77, .10, .27, .42). These estimates are well within the confidence intervals in Table 5. Using a VECM(8), the real component explains somewhat less of the variability in y and c at horizons 1-20, while the nominal factor increases in importance. As in the three variable case, conventional tests indicate that 4 lags are adequate. For example, the likelihood ratio test for 4 vs. 8 lags (using Sims' [1980] correction) has an asymptotic p-value of .57. The F-statistics for the individual equations in the test of 4 vs. 8 lags have p-values of: y, .45; c, .68; i, .29; m, .23; and p, .16.

19. Denison's measure of potential output is computed by adjusting actual output using an Okun's law relationship, adjusting for capacity utilization, and by making other adjustments such as for labor disputes, the weather, and the size of the armed forces. Source: Denison (1985), Table 2-4.

20. For recent discussion of Solow's measure of technical progress, see Hall (1986) or Prescott (1986).

21. We are grateful to Gary Hansen for providing us with his adjusted hours series and Prescott's Solow residual series.

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Appendix

Common Trends and Cointegration

This appendix presents the derivation of the "common trends" model (3.1) from Engle and Granger's (1987) cointegrated model. Suppose that the n×1 vector X_t has a moving average representation in first differences, perhaps with a nonzero n×1 drift δ:

$$\text{(A.1)} \qquad \Delta X_t = \delta + C(L)\epsilon_t$$

where $E(\epsilon_t|X_s, s<t)=0$, $E(\epsilon_t\epsilon_r'|X_s, s<\max(t,r))=0$, $t\neq r$, and $=\Sigma$, $t=r$. Engle and Granger (1987) define X_t to be cointegrated if there exists some n×1 vector α such that $\alpha'X_t$ is stationary; here, this implies that $\alpha'\delta=0$ and $\alpha'C(1)=0$. We assume that there are n-k such cointegrating vectors. It will be shown that X_t has a common trends representation with k common stochastic trends. Expanding (A.1),

$$\text{(A.2)} \qquad X_t = X_o + \delta t + C(1)\xi_t + D(L)\epsilon_t$$

where $D_j=-\sum_{i=j+1}^{\infty}C_i$ and $\xi_t=\sum_{s=1}^{t}\epsilon_s$ so that ξ_t is a n×1 random walk with serially uncorrelated innovations ϵ_t. Since $\alpha'\delta=0$ and $\alpha'C(1)=0$, the cointegrating residual or "error correction" term has the representation,

$$\text{(A.3)} \qquad \alpha'X_t = \alpha'X_o + \alpha'D(L)\epsilon_t\ .$$

To derive the common trends representation from (A.2), note that since $C(1)$ has rank k, it has n-k eigenvalues that equal zero. Let $H^{-1}JH$ denote the Jordan canonical form of $C(1)$, where the columns of H^{-1} are the eigenvectors of $C(1)$ and J is a block diagonal matrix with the eigenvalues of $C(1)$ on its diagonal. Since $C(1)$ has rank k, it has n-k zero eigenvalues and J can be partitioned as:

$$J = \begin{bmatrix} J_{11} & 0 \\ 0 & 0 \end{bmatrix} \quad , \quad H^{-1} = (H^1 \; H^2) \qquad H = \begin{bmatrix} H_1 \\ H_2 \end{bmatrix}$$

where J_{11} is a nonsingular kxk matrix and where H and H^{-1} are partitioned conformably with J, so that H_1 is kxn. Note that $H_1C(1)=J_{11}H_1$ and $H_2C(1)=0$. Thus the rows of H_2 are a basis of the cointegrating vectors of X_t. With these definitions, $C(1)\xi_t=H^{-1}JH\xi_t=H^1J_{11}H_1\xi_t$. By the definition of cointegration, since $\alpha'\delta=0$ and $\alpha'C(1)=0$, δ must also lie in the column space of H^1, so that it can be written as $\delta=H^1\bar{\mu}$, where $\bar{\mu}$ is some kx1 vector. Combining these expressions for $C(1)\xi_t$ and δ, (A.2) can be written,

$$\begin{aligned} X_t &= X_o + H^1\bar{\mu}t + H^1J_{11}H_1\xi_t + D(L)\epsilon_t \\ &= X_o + H^1(\bar{\mu}t + J_{11}H_1\xi_t) + D(L)\epsilon_t \\ &= X_o + H^1\bar{\tau}_t + D(L)\epsilon_t \qquad \text{(A.4)} \end{aligned}$$

where $\bar{\tau}_t=\bar{\mu}t+J_{11}H_1\xi_t=\bar{\mu}+\bar{\tau}_{t-1}+\bar{\eta}_t$, where $\bar{\eta}_t=J_{11}H_1\epsilon_t$.

The innovations $\bar{\eta}_t$ have nondiagonal covariance matrix $E\bar{\eta}_t\bar{\eta}_t'=J_{11}H_1\Sigma H_1'J_{11}'=Q$. Defining η_t to be the transformed innovations $\eta_t=Q^{-\frac{1}{2}}\bar{\eta}_t$, where $Q^{\frac{1}{2}}Q^{\frac{1}{2}\prime}=Q$, $E\eta_t\eta_t'=I_k$. Thus (A.4) can be rewritten in the common trends form,

$$X_t = \gamma + A\tau_t + D(L)\epsilon_t \tag{A.5}$$

where $\gamma = X_0$, $\tau_t = \mu + \tau_{t-1} + \eta_t$, $\mu = Q^{-\frac{1}{2}}\bar{\mu}$ and $A = H^1 Q^{\frac{1}{2}}$.

The permament and transient innovations are related by $\eta_t = F\epsilon_t$, where $F = Q^{-\frac{1}{2}} J_{11} H_1$, so that $E\eta_t \epsilon_t' = F\Sigma = Q^{-\frac{1}{2}} J_{11} H_1 \Sigma$. Thus the correlation between the permanent and transitory shocks depends on the nonzero Jordan block of C(1), its corresponding eigenvectors, and the covariance matrix of the transitory innovations themselves. In the multivariate case considered here, the "factor loadings" of the different trends are given by $H^1 Q^{\frac{1}{2}}$ or, in the notation of (A.5), by A. In the univariate case, this Common Trends representation reduces to the stationary/nonstationary decomposition proposed by Beveridge and Nelson (1981).

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