LONG RUN EFFECTS OF BUSINESS CYCLES

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ABSTRACT

This paper investigates the interaction between economic fluctuations and productivity. A simple theoretical model and an associated empirical VAR model are developed, in which two types of shocks—"technology" and "demand" shocks—affect the dynamics of a measure of productivity and an index of the business cycle. Identification is achieved by assuming that demand shocks have no contemporaneous effect on productivity. Using U.S. data, we find that positive demand shocks have a negative long run impact on productivity. That result is robust to the measure of productivity and the cyclical indicator used. A number of interpretations are discussed and related to the existing literature.

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1. Introduction

Macroeconomists have traditionally interpreted movements in GNP and other aggregate time series as having two basic components: (i) a smooth upward trend, and (ii) recurrent, transitory fluctuations about it, i.e. business cycles. Under that view, long term growth was ultimately driven by technical progress reflected in steady increases in productivity, whereas short term fluctuations were mostly the result of changes in aggregate spending or monetary variables. Both components were perceived as being different in nature and largely independent, each having a life of its own.

Such a dichotomous view of growth and business cycles has been challenged in the recent literature. First, as originally shown by Nelson and Plosser (1982), most macroeconomic variables seem to be characterized by the presence of a unit root in their stochastic component, implying that one or more sources of economic fluctuations may have permanent effects, and thus questioning the transitory nature of those fluctuations. On the other hand, the Real Business Cycle literature (e.g., Kydland and Prescott (1982)) has stressed the potential role of exogenous variations in productivity as a cause of short term fluctuations, as well as long term growth, thus breaking the traditional dichotomy.

Finally, recent developments in growth theory have stressed the endogenous nature of productivity growth (e.g., Lucas (1988), Romer (1990)), as the outcome of optimal decisions concerning the accumulation of knowledge or human capital, decisions which are generally affected by the economic environment. That gives rise to the possibility that economic fluctuations—when caused by forces other than technology shocks—may in turn have an effect on productivity, by altering incentives in those decisions.

This paper is an attempt to investigate empirically the nature of this interaction between productivity and business cycles in a framework which allows for both directions of causality. Supposing that variations in aggregate demand or other non-technology shocks are an important source of fluctuations, what effects could they have on productivity? There are three possible answers:

1) Productivity growth may be exogenous to factors that are at work over the business cycle, and will not be affected by them. As mentioned above, this view underlies traditional interpretations of growth and fluctuations, and is still implicit in a large number of business cycle models[1].

2) "Booms" may have a positive effect on productivity through a "learning by doing" mechanism, for they are periods when workers and firms "learn" unusually fast because of their high levels of activity[2].

3) Alternatively, it may be recessions rather than expansions that improve productivity. Recessions may be a time when the opportunity cost of improving productivity is relatively low (e.g. Hall (1991), Aghion and Saint-Paul (1991)). They may also improve average productivity by turning the most inefficient production units unprofitable and weeding them out (Caballero and Hammour (1991)). We loosely term this broad class of phenomena—by which recessions lead to the reallocation of resources toward productivity-enhancing activities and/or away from less productive activities—the "reallocation" effect of recessions.

In section *2*, we propose a simple illustrative theoretical model that can accommodate the three previous hypotheses concerning the effect of economic fluctuations on productivity. We construct a two-sector endogenous growth model, augmented with shocks to technology and preferences. The sign of the response of productivity to preference shocks is shown to depend on the relative size of parameters measuring the "learning by doing" and the "reallocation" effects.

The main results of the paper are contained in section *3*. In that section we address the

[1] Included in this category are models in which technology shocks are the main driving force of business cycles (e.g. Kydland and Prescott (1982)), as well as other models in which technology is constant and where fluctuations are driven by shocks of a different nature, such as fiscal policy shocks (e.g. Christiano and Eichenbaum 1990), sunspot events (e.g. Woodford 1991), etc.

[2] See Arrow (1962) for an early discussion of learning-by-doing in a deterministic model. Recent examples of business cycle models with learning-by-doing include Christiano and Eichenbaum (1988) and Stadler (1990).

above issue empirically, using a VAR model of the joint behavior of aggregate productivity growth and a cyclical indicator for the U.S. economy. Our measure of productivity growth is the Solow residual, with several adjustments for such factors as labor hoarding, market power or increasing returns. Our main index of the business cycle is the employment rate, but we obtain similar results with capacity utilization. Taking the model in section *2* as a reference, we assume there are two major types of exogenous, aggregate shocks in the economy. One of them is a "technology" shock that has a contemporaneous effect on productivity. The other is a shock that has no contemporaneous effect on productivity, and that we think of as a "demand" shock.

The estimated impulse response functions show that a positive technology shock increases employment temporarily and has a permanent positive effect on productivity, in a way consistent with the predictions of standard RBC models[3]. More interestingly, a positive aggregate demand shock increases employment temporarily, but *lowers* productivity in the long run. This supports the idea that "reallocation" effects are stronger than "learning by doing" effects. Those results appear to be robust to the measures of productivity and the cyclical indicator used, as well as to the sample period considered. Interestingly, we can use our model to decompose historical variations in productivity and employment into components due to supply and demand shocks. The resulting decomposition seems consistent with traditional interpretations of American business cycle history.

In section *4* we discuss alternative interpretations of our results, and relate them to the literature. We then choose to focus on one potential channel through which recessions may improve productivity, namely the hypothesis that recessions are a time when the opportunity cost of building human capital is relatively low. First, we look for direct evidence for whether human capital accumulation—either through the job training of hoarded labor or through formal schooling—is in fact countercyclical. Second, we try to get a measure of changes in embodied human capital by turning to the quality-adjusted labor and capital input series constructed by

[3] King et al. (1991) give an example of an RBC model with this type of non-stationary technology.

Jorgenson, Gollop and Fraumeni (1987). We repeat the exercise of section *3* using those new time series, but find that our results are unaffected by this adjustment. There seems to be little evidence that the human capital channel plays an important role in explaining the effect of demand shocks on productivity.

Section *5* summarizes the paper and concludes.

2. Business Cycles and Productivity Growth: an Illustrative Model.

a) The Model

We propose a simple variation on the two-sector model of endogenous growth, augmented with exogenous shocks to technology and preferences[4].

The representative consumer/producer is infinite-lived and maximizes the expected present discounted value of utility

$$U = E_0 \sum_{t=0}^{\infty} \beta^t u(C_t) \exp(Z_t)$$

where β is the discount factor, C_t is consumption at time t, and the utility function $u(.)$ is of the CRRA form with a relative risk aversion coefficient $\sigma > 0$. The stochastic term Z_t captures exogenous preference shocks, and is assumed to follow a process

$$Z_t = \rho_z Z_{t-1} + \varepsilon_{z,t} \qquad 0 \le \rho_z \le 1.$$

Our consumer is endowed with one unit of time per period. In period t, a fraction N_t of that time is spent in the production of a perishable good, and yields output

$$Y_t = A_t B_t N_t, \tag{1}$$

which is equal to consumption C_t in equilibrium. Physical capital is ignored for simplicity. A_t represents the exogenous component of productivity that is freely available to all agents. It evolves over time according to

[4] A version of this model with both physical and human capital but only supply shocks is analyzed by King and Rebelo (1988). For a deterministic version of this model, see Uzawa (1965) and Lucas (1988).

$$(A_t / A_{t-1}) = \exp(X_t), \tag{2}$$

where X_t follows a process

$$X_t = \rho_x X_{t-1} + \varepsilon_{x,t} \qquad 0 \le \rho_x \le 1.$$

B_t is the endogenous component of productivity, and can be either embodied or disembodied. Its rate of accumulation is given by

$$(B_{t+1} / B_t) = \alpha - \theta N_t + \tau \tilde{N}_t,$$

where $\tilde{N}_t$ denotes (per capita) aggregate hours, and can thus be thought of as an index of aggregate activity which our representative agent takes as given[5].

This specification embeds simple versions of the three hypotheses discussed in the introduction, concerning the effects of demand shocks on productivity:

1) By setting $\theta = \tau = 0$ and $\alpha \ge 1$, the model collapses into an exogenous growth model. The total productivity growth rate is given by the exogenous stochastic process $\alpha + X_t$, and is unaffected by preference shocks.

2) The external "learning by doing" effect can be introduced in a stylized manner by setting $\tau > 0$ (internal learning by doing can also be introduced if we assume $\theta < 0$, but this possibility is not considered below).

3) Finally, as will be shown, the "reallocation" effect of recessions arises in the case where $\tau = 0$ and $\theta > 0$. The endogenous component B_t of productivity can be very broadly understood, but one way to interpret it is as embodied human capital. In this case, setting $\tau = 0$, $\theta > 0$ and $\alpha = (1-\delta) + \theta$ gives us Lucas' (1988) model of human capital accumulation, where δ is the depreciation rate of human capital.

Assuming an interior solution for the consumer's problem[6], the symmetric equilibrium for the

[5] We attribute the constant trend in productivity exclusively to B. This is done for notational simplicity, and leads to no loss of generality.

[6] Given that we have ignored, for convenience, the possibility that leisure yields utility, an interior solution requires that $\theta > 0$, otherwise it would be optimal for the consumer to choose the corner solution $N_t = 1$, for all t. Given "small enough" shocks, an interior solution can be shown to be guaranteed if $[\alpha+(\tau-\theta)N]^{\sigma} = \beta(\alpha+\tau N)$ is solved for some $0<N<1$. The solution to that equation is just the value of N along the perfect foresight balanced growth path.

economy above is characterized by the Euler equation

$$u'(Y_t)\, exp(Z_t)\, A_t = E_t\{\beta\, u'(Y_{t+1})\, exp(Z_{t+1})\, (\alpha+\tau N_{t+1})A_{t+1}\}, \tag{3}$$

the aggregate production function (1), and the dynamics for A and B, determined respectively by (2) and

$$(B_t \,/\, B_{t-1}) = \alpha + (\tau - \theta)\, N_{t-1}, \tag{5}$$

since, in the symmetric equilibrium, $N_t = \bar{N}_t$. To those conditions we must add the above $AR(1)$ specifications for $\{X_t\}$ and $\{Z_t\}$, and the transversality condition $\lim_{T\to\infty} E_0\, \beta^T\, u'(Y_t)\, B_t = 0$.

In the absence of exogenous shocks—i.e. $Z_t = X_t = 0$, for all t—the economy is always on a balanced growth path with constant N^*, and a constant growth rate $\gamma = \alpha+(\tau-\theta)N^*$ for B and Y. For the stochastic economy, equilibrium dynamics can be characterized as deviations from that balanced growth path, using the log-linear approximation methods described in King, Plosser and Rebelo (1988).

Given the purpose of this section, we restrict our attention to the equilibrium dynamics of two variables: N_t—a natural cyclical indicator in our model—and the growth rate $\Delta s_t \equiv s_t - s_{t-1}$ of total productivity, where $s_t \equiv ln\ A_t B_t$. We let N^* and Δs^* denote employment and total productivity growth along the balanced growth path, and define $\Delta s'_t = (\Delta s_t - \Delta s^*)$ and $N'_t = (N_t - N^*)$ as the deviations from those values. It is not difficult to show that the linearized dynamics of $\{\Delta s'_t, N'_t\}$ have the following representation in terms of the exogenous processes $\{X_t\}$ and $\{Z_t\}$:

$$\begin{bmatrix} \Delta s'_t \\ N'_t \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ \phi_x & \phi_z \end{bmatrix} \begin{bmatrix} X_t \\ Z_t \end{bmatrix} + \begin{bmatrix} (\tau-\theta)\phi_x & (\tau-\theta)\phi_z \\ 0 & 0 \end{bmatrix} \begin{bmatrix} X_{t-1} \\ Z_{t-1} \end{bmatrix} \tag{6}$$

where $\phi_x \equiv \Omega_x(\sigma-1)N^*\rho_x/\gamma$ and $\phi_z \equiv \Omega_z N^*(1-\rho_z)/\gamma$, with $\Omega_i \equiv [\sigma(\theta-\tau)N^*/\gamma + \rho_i\tau N^*/(\alpha+\tau N^*) + \sigma(1-\rho_i)]^{-1}$, for $i = X, Z$.

b) *Effects of Technology and Demand Shocks*

How do productivity and employment respond to different types of shocks? Not surprisingly, and as (6) makes clear, both the sign and the magnitude of that response will depend on the

particular parameter configuration. We discuss below some of the possible responses allowed by the model. We limit ourselves to the case in which the learning by doing parameter τ is not "too large", so that both Ω_x and Ω_z are positive[7].

First, consider the economy's response to a favorable technology shock, i.e. one that increases X temporarily. In the absence of any persistence ($\rho_x=0$) we have $\phi_x = 0$, and the impact of that shock will be limited to a trivial direct exogenous effect on productivity. When $\rho_x > 0$, employment and, as a consequence, the endogenous component of productivity will also be affected. If $\sigma > 1$, the response of employment to an increase in X will be positive, and the induced response of endogenous productivity will either amplify or dampen the shock's initial impact on productivity, depending on whether the "learning by doing" effect dominates the "reallocation" effect (i.e. $\tau>\theta$), or vice versa. If $\sigma < 1$, the effect of technology shocks on N_t and their induced effect on endogenous productivity are reversed. Substitution effects dominate in this case, and our representative agent allocates more resources to improving endogenous productivity B in response to a positive technology shock.

Let us turn to the effects of a positive preference shock, that raises Z. As long as $\rho_z < 1$, such a shock will lead to an increase in employment. Given the change in employment, its subsequent impact on productivity depends exclusively on the sign and size of $(\tau-\theta)$, i.e. on the relative importance of the "learning by doing" vs. the "reallocation" effect. If the former is stronger ($\tau>\theta$) the demand-driven expansion will lead to a net increase in the pace of learning, and have a permanent positive effect on productivity. On the other hand, if the "reallocation" effect dominates ($\theta>\tau$), the boom shifts resources towards current goods production and away from productivity-enhancing activities. Though temporary, that reallocation leads to a permanent decrease in the level of productivity.

The above model illustrates the different possible channels of interaction between

7 It can be shown that Ω_x and Ω_z are positive when $\tau = 0$. By continuity, they remain positive for a small enough τ.

productivity growth and business cycles. It will be kept as a reference framework for the empirical investigation below. The essential features we will rely on are, first, the assumption of two major types of exogenous shocks in the economy—"technology" shocks $\varepsilon_{x,t}$ and "demand" shocks $\varepsilon_{z,t}$—that affect the dynamics of productivity growth Δs_t and a business cycle index N_t. Using the fact that $X_t = (1-\rho_x L)^{-1}\ \varepsilon_{x,t}$ and $Z_t = (1-\rho_z L)^{-1}\ \varepsilon_{z,t}$, we can rewrite (6) as a distributed lag of the white noise vector $\varepsilon_t \equiv [\varepsilon_{x,t}, \varepsilon_{z,t}]'$:

$$\begin{bmatrix} \Delta s'_t \\ N'_t \end{bmatrix} = \begin{bmatrix} C_{11}(L) & C_{12}(L) \\ C_{21}(L) & C_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{x,t} \\ \varepsilon_{z,t} \end{bmatrix} \equiv C(L)\ \varepsilon_t \tag{7}$$

Second, one of the restrictions imposed by the model on (7) takes a particularly simple form, namely, $C_{12}(0) = 0$, i.e. "demand" shocks $\varepsilon_{z,t}$ do not have a contemporaneous effect on productivity Δs. Equation (7) combined with this restriction form the basis of the following empirical analysis.

3. Business Cycles and Productivity Growth: a Simple Macroeconometric Framework.

In this section we use U.S. aggregate time series to characterize the interaction between productivity and the business cycle, taking the framework developed in the previous section as a reference. Our approach shares some features with the "structural" VAR literature[8].

a) Specification

Consider a vector sequence $\{(\Delta s_t, N_t)\}_{t=0}^{\infty}$ where Δs is a measure of multifactor productivity

[8] Early contributions to this literature include Bernanke (1986), Blanchard and Watson (1986) and Sims (1980). As in all of those references, this paper relies on short-run identifying restrictions. More recent work by Blanchard and Quah (1989) and Shapiro and Watson (1988) uses long-run restrictions. Galí (1992) uses both types of restrictions.

growth, and N is a "cyclical indicator", i.e. a macroeconomic time series whose variability is concentrated at business cycle frequencies. An example of such a variable, extensively used below, is the employment rate (i.e., one minus the unemployment rate). Another example is capacity utilization. For ease of exposition we will refer to N as "employment", though it should be clear that it can represent other variables.

As in section 2, we remove the mean of both Δs and N, and let $\Delta s'$ and N' denote the resulting variables. In a way consistent with the model in that section, we assume that $\{(\Delta s'_t , N'_t)\}_{t=0}^{\infty}$ is a (zero mean) stationary stochastic process, driven by two types of exogenous forces: (i) technology shocks, represented by a sequence $\{\varepsilon_{x,t}\}_{t=0}^{\infty}$, and (ii) demand shocks, represented by $\{\varepsilon_{z,t}\}_{t=0}^{\infty}$. The dynamic behavior of $\Delta s'$ and N' can thus be described by the distributed lag model in (7).

Both ε_x and ε_z are assumed to have zero mean, and to be serially and mutually uncorrelated at all leads and lags. Without loss of generality we normalize their variances to unity, so we have $E\varepsilon_t\varepsilon'_t = I$, for all t. We refer to these shocks as the "fundamental" shocks driving the economy's fluctuations.

The central goal of this section is to estimate $C(L)$ and recover the impulse responses of Δs and N to each of the fundamental shocks. The model is identified by a restriction consistent with our theoretical model: *demand shocks* ε_z *do not have a contemporaneous effect on productivity*. Formally, we assume $C_{12}(0) = 0$. Naturally, the level of activity in period t may still affect the level of productivity in period $t+1$. On the other hand, technology shocks are allowed to affect productivity and employment contemporaneously. Clearly, our identifying restriction allows for endogenous productivity and, in particular, for a *permanent* effect of *both* types of shocks on the level of productivity[9].

[9] Given the assumption of a unit root in s (justified empirically below), at least one of the shocks must have a permanent effect on the level of this variable. By allowing for a permanent effect of demand shocks on productivity we depart from the identification strategy adopted, among others, by Blanchard and Quah (1989), Shapiro and Watson (1988) and Galí (1990), and which consisted in restricting demand shocks not to have a permanent effect on output.

Technical details of the identification and estimation procedures are given in appendix 1. The rest of this section discusses the empirical counterparts of s and N and our main empirical results.

b) Measures of Cyclical Indicators and Productivity

We use both quarterly and annual U.S. data. Available data allow us to present results based on quarterly data for the "postwar" period 1947:1-1989:4, and on annual data for the "full" sample period 1890-1987. Our basic results turn out to be robust to the frequency and sample period used.

The main aggregate series we use as a "cyclical indicator" is the employment rate (i.e., one minus the unemployment rate). This measure is denoted by $N(er)$ in the tables below. We also present results for the postwar period using the rate of capacity utilization in the manufacturing sector, denoted by $N(cu)$[10].

As for productivity, our empirical counterpart for Δs is the (log) first difference of multifactor productivity (MFP) in the private business sector. With an aggregate production function in mind, growth in MFP can be measured by the Solow residual (Solow (1957)). Unfortunately, that measure is flawed if there are serious measurement problems, or if some of Solow's underlying assumptions are violated. In particular, it has been argued that the procyclicality of the Solow residual is evidence of such a problem[11], and can be due to labor hoarding (Fair (1969)) or to increasing returns and/or market power (Hall (1990)).

In order to take these different possibilities into account, we construct three alternative

[10] Yearly total unemployment rates: for the 1890-1928 period, we use the Lebergott series, as reported in U.S. Bureau of Economic Analysis (1973); for 1929-1987 we use the BLS series found in the Economic Report of the President.

Quarterly total civilian unemployment rates: we use averages of the monthly, seasonally adjusted BLS series obtained from Citibase, 1948:1-1989:4.

Quarterly capacity utilization: total manufacturing, seasonally adjusted, 1948:1-1989:4, constructed by the Board of Governors of the Federal Reserve, extracted from Citibase.

[11] In the Real Business Cycle literature, the procyclicality of the Solow residual has often been interpreted as evidence of the importance of technology shocks, and has been used accordingly for calibration purposes (e.g., Prescott (1986)).

MFP measures: a "standard", a "labor hoarding" and an "IRS-market power" measure. They are derived and discussed in detail in appendix 2. We checked for the robustness of our results by conducting extensive sensitivity analysis for each of those measures. The main conclusion is that our basic qualitative results are quite robust and independent of the measure productivity used. Our three alternative productivity measures are described below, and are derived and discussed in further detail in appendix 2.

a) The "standard" measure of productivity corresponds to the Solow residual (Solow (1957)), defined as

$$\Delta s_t \equiv \Delta y_t - [\alpha_t \Delta h_t + (1-\alpha_t)\Delta k_t]$$

where α is the share of labor income in GNP, y is (log) GNP, h is (log) hours and k is (log) capital[12]. The corresponding measure of s is shown in the top panel of Figure 1.

b) The "labor hoarding" measure of productivity is adjusted for cyclical variations in the rate of labor utilization (see, e.g., Gordon (1990); Burnside, Eichenbaum and Rebelo (1990)[13]). The measure we use, derived in the appendix, is given by

$$\Delta s_t \equiv \Delta y_t - [\alpha_t \Delta h_t + (1-\alpha_t)\Delta k_t] - [\varphi/(1-\varphi)]\ \alpha_t \Delta \hat{H}_t$$

where $\hat{H}$ denotes percent deviations of measured hours from trend, and φ is the fraction of short run changes in *effective* labor input that is not captured by changes in measured hours.

What are reasonable values of φ ? As is well known, estimates of φ obtained by running an OLS regression of the Solow residual on $\Delta\hat{H}$ will generally be inconsistent because of non-zero correlation between $\Delta\hat{H}$ and random variations in productivity. Furthermore, our hypothesis of endogenous productivity rules out the use of exogenous variables like those suggested by Hall (1990) as instruments, for any variable that affects the level of economic activity may have an

[12] Data sources for the annual MFP series: For the period 1948-1987 we use the measure of MFP for the private business sector published by the Bureau of Labor Statistics. For the early part of the sample we draw on the MFP series constructed by Kendricks, and reported in U.S. Bureau of Economic Analysis (1973).

Data sources for the quarterly MFP series: We use the seasonally adjusted quarterly series used to construct the BLS measure of MFP for the private business sector (Source: Citibase).

[13] Burnside, Eichenbaum and Rebelo (1990) introduce labor hoarding and variable effort in a real business cycle model with stochastic technology and government purchases.

impact on productivity, thus losing its status as an admissible instrument. Fortunately, some direct evidence on the value of φ can be found in the work of Fay and Medoff (1985). Their results, based on a survey of U.S. firms, imply an average value for φ equal to 0.21 [14]. We use that value to compute our benchmark measure of productivity growth adjusted for labor hoarding, and conduct sensitivity analysis with φ values between 0.1 and 0.3 [15]. A plot of the corresponding benchmark s series can be found in Figure 1.

c) Finally, the "IRS-market power" measure generalizes the original Solow residual by allowing for simple forms of increasing returns and/or market power (Hall (1990)). The following expression is derived in the appendix:

$$\Delta s_t \equiv \Delta y_t - \gamma \{ (\mu/\gamma)\alpha_t \Delta h_t + [1-(\mu/\gamma)\alpha_t] \Delta k_t \},$$

where values of γ and μ that are greater than one are evidence of increasing returns and market power, respectively.

Again, estimation of γ and/or μ by an OLS or IV procedure—the approach followed in Hall (1990)—is not appropriate under our assumptions, for the reasons given above. Instead, our approach takes advantage of the tight theoretical bounds on the ratio (μ/γ), which must lie in the interval $(1,1/\alpha)$ (see appendix 2)[16]. Given an admissible value for (μ/γ), we determine an upper bound for γ by constraining the resulting measure of productivity growth to have a non-negative average over sufficiently long periods of time. Our benchmark productivity measure in this case is based on values $(\mu/\gamma) = 1$ and $\gamma = 0.3$, and is also plotted in Figure 1. We view a value of γ equal to 0.3 as a "natural" upper bound: higher γ values would imply persistent "technological regression" in the early and late parts of our sample period, as becomes clear by looking at Figure 1. None of our main results turn out to be sensitive to the choice of μ and γ

[14] This value is obtained by dividing the average "percentage of normal labor hours that technically could have been eliminated but were not" by the average "technically possible percentage reduction in total labor hours" in table 2 in Fay and Medoff (1985). See that reference for further discussion.

[15] We use a second-order polynomial of time to detrend (log) measured hours and construct the $\hat{H}$ time series.

[16] The average value of $(1/\alpha_t)$ for the full sample is 1.46.

in the admissible range.

c) *Unit Root Tests.*

Our model specification in (7), based on the theoretical model of section 2, implies that $\{s_t\}_{t=0}^{\infty}$ and $\{N_t\}_{t=0}^{\infty}$ are, respectively, an *I(1)* and an *I(0)* process. Table 1 reports the results of several unit root tests on the time series introduced above. For each series and frequency we compute the Augmented Dickey-Fuller *t*-statistic (Dickey and Fuller (1979)) for the null of a unit root against a trend-stationarity alternative.

The results are consistent with our specification. A unit root in s, the log of multifactor productivity, cannot be rejected at the 5 percent significance level regardless of the particular measure used, while the null of a unit root in Δs is systematically (and strongly) rejected. Taken together, these results suggest that our s measures can be reasonably modeled as an *I(1)* process. On the other hand, unit roots in *N(er)* and *N(cu)*—the latter limited to the postwar period—are rejected at the 5 percent level[17]. Both cyclical indicators can thus be modeled as *I(0)* processes[18].

d) *Granger Causality Tests.*

Much of the analysis and discussion in this paper evolves around the idea of endogenous productivity. In the context of the model in (7) this corresponds to $C_{12}(L) \neq 0$. If $C_{12}(L) = 0$, productivity is exogenous, in the sense that it is unaffected by shocks other than technology shocks. The latter property is an underlying assumption in most real business cycle models

[17] A unit root in *N(er)* cannot be rejected for the *prewar* period alone (1890-1947), though the size of the *t*-statistic in this case (-2.74) does not provide strong evidence in favor of the unit root null. This result is not surprising, given the strong persistence in employment generated by the Great Depression.

[18] With the exception of *N(er)* for the full sample period, the linear time trend shows up significantly in the ADF regressions applied to the different N measures. Accordingly, the *N(er)* and *N(cu)* measures used in what follows are deviations from the estimated linear trend.

(e.g., Brock and Mirman (1972), Kydland and Prescott (1982)). Interestingly, the hypothesis of "exogenous technology" generates a simple, testable prediction in terms of our model: N should not Granger-cause Δs. Furthermore, under the identifying assumption introduced above, the lack of Granger-causality from N to Δs implies that productivity is exogenous. In other words, lack of Granger-causality from N to Δs is both a necessary and sufficient condition for productivity to be exogenous in our model (see appendix 1). Thus, establishing Granger-causality is equivalent to formally rejecting the exogenous productivity hypothesis[19].

As a preliminary check of the plausibility of our model with endogenous productivity we conduct some Granger-causality tests. The main results are summarized in table 2, which reports the significance levels at which the null of no Granger-causality is rejected, for different measures of both variables and alternative sample periods. For each case two values are reported, corresponding to regressions with one and four lags.

The hypothesis that N does not Granger-cause productivity growth is rejected at very low significance levels for the postwar period. This result is robust to the measure of N and s used. The results for the full sample period are less strong. When only one lag of N and Δs is included in the regression, the p-values for the Granger-causality test are still low (less than 7 percent in all cases). But in the regression with four lags the p-values are substantially higher than conventional levels, especially when the "labor hoarding" and "IRS-market power" measures of productivity are used[20].

e) Impulse Response Estimates

[19] Bean (1990) and Evans (1991) show a related application of Granger-causality tests as tests of endogeneity of productivity.

[20] In independant research, Evans (1991) showed that the Solow residual is Granger-caused by a number of macroeconomic aggregates (money supply, interest rates, government expenditure, etc.). Since we are not specifying the source of our aggregate demand shock, and given the known cyclicality of those aggregates, his results are consistent with ours. Furthermore, Evans interprets his results as suggesting the presence of labor hoarding and/or increasing returns. We obtain similar results for measures of multifactor productivity that correct for those factors. Thus, our results are suggestive of "true" endogeneity of multifactor productivity.

We now turn to the estimated impulse response functions of productivity and employment for different sample periods and alternative measures of Δs and N [21].

Figures 2a and 2b plot the estimated full-sample period impulse response functions with the "standard" and "labor hoarding" measures of Δs, respectively, and with the cyclical indicator *N[er]*. The impulse response function that corresponds to the "IRS-market power" measure is virtually identical to Figure 2b and is thus omitted. A one standard error band is drawn around the point estimates[22]. All the impulse responses correspond to a one standard deviation shock.

The dynamic response to a favorable technology shock are consistent, qualitatively, with the predictions of the model in section 2 under the assumption of a low elasticity of substitution (σ>1) for, as a result of a positive technology shock, employment rises and then slowly returns to its initial level. The initial impact of the technology shock on employment is larger for the "standard" measure of productivity (about 1.4 percent) than it is for the "labor hoarding" measure (about 0.9 percent).

The effects of demand shocks are perhaps more striking. Irrespective of the measure of productivity that we use, we find that a demand shock that raises the employment rate by more than 2 percentage points causes the level of s to decrease steadily, and leads to a permanent reduction in the level of productivity of about 1.4 percent. In other words, the estimates suggest that demand-driven expansions have a permanent *negative* effect on the level of multifactor productivity, while recessions have a *positive* effect. Of course, the symmetry of those effects follows from to the model's linearity. The reader will recall that those results correspond to the predictions of our model under the assumption that the "reallocation" effect dominates the "learning by doing" effect[23].

[21] We use a one year lag structure in the VAR model for $[\Delta s\ , N]$, i.e. one lag when yearly data are used, and four lags for quarterly data. Qualitatively, our results are essentially unchanged when higher-order lags are used.

[22] Standard errors are obtained through a Montecarlo procedure based on normal random drawings from the distribution of the reduced form VAR. The standard errors for the $C(L)$ coefficients are based on the Q-transformation (see appendix for a definition of Q) of each draw, and are thus conditional on the initial estimate of $\hat{Q}$.

[23] Using our VAR approach, Saint-Paul (1993) obtains a similar qualitative result for a

This last result seems to be very robust to the measure of productivity that we choose, and to different values of φ, γ and μ that we tried. We also found it to be qualitatively robust to the choice of cyclical indicator (*N[cu]* vs. *N[er]*) and to the sampling frequency. To illustrate, figures 3a and 3b give the equivalent results to figures 2a and 2b, but now for the post-war *quarterly* series. The qualitative results are clearly the same.

f) Historical Decompositions.

In this section we decompose the historical time series for productivity and employment into two components, associated with technology and demand shocks respectively. Thus, for instance, the "technology component" of productivity growth at time t is given by the estimate of $C_{11}(L)\varepsilon_t$ [24]. The results we report here were obtained for the full-sample annual series using the "labor hoarding" measure of productivity. Figures 4a and 4b show the decomposition of productivity and employment for the prewar (1890-1947) and the postwar (1948-1987) periods, respectively.

In order to compare our results with more informal interpretations, we indicated NBER business cycle "trough" years by a vertical line. It is clear that they correspond very closely to "trough" years for the demand component of employment. The relation with the productivity component is much less clear. In fact, demand shocks seem to play a much greater role in explaining employment variability than supply shocks.

In particular, the Great Depression and subsequent recovery seem to be due solely to demand factors. They are estimated to have produced an acceleration and then a deceleration in productivity growth. The long expansion of the 1960s and the 1982 recession are also largely explained by demand factors. Interestingly, the 1960s expansion seems to have played an important role at the start of the "productivity slowdown" episode, but not in a later stage.

majority of O.E.C.D. countries.

[24] We include the deterministic drift in both components of productivity. Thus we can interpret the "demand" component as the productivity series that we would observe if we set all "technology" shocks to zero.

However, if we turn to the 1970s, we find that productivity shocks related to the two oil shocks of the 1970s play a significant role in explaining movements in employment.

4. Some Possible Interpretations

a) Possible Interpretations

We now turn to possible explanations of the "reverse effect" that demand shocks seem to have on productivity, a result that in the context of the model in section 2 is associated with strong "reallocation" relative to "learning by doing" effects. We can think of two broad types of explanations: "cleansing" and "opportunity cost" explanations.

According to the first type, recessions have a "cleansing" effect on the productive system, for they may cause less efficient production units to become unprofitable and shut down. As a consequence, the average level of productivity will improve. This idea goes back to the "liquidationist" view of economic fluctuations associated with Schumpeter and Hayek (DeLong (1990)), but it does not necessarily entail that recessions are desirable events. Recently, Caballero and Hammour (1991) have analyzed the cleansing effect of recessions in a model of "creative destruction," where production units that embody the newest techniques are continuously being created and outdated units are being destroyed. When there are reasons to smooth out the creation process over the business cycle, a fall in demand increases the rate at which outdated production units are scrapped, thus increasing the average productivity of units in operation.

The second type of explanations relies on the idea that recessions are a time when the "opportunity cost" of undertaking productivity-enhancing activities is relatively low. Recessions may be, for example, the right time for trying to improve the match between workers and firms (Davis and Haltiwanger (1990)), or for reorganization and the implementation of new technologies (Hall (1991), Aghion and Saint-Paul (1991)). They may also be the right time to build human capital, either through the job training of hoarded labor or even through formal schooling.

This last explanation, in which human capital investment is countercyclical, will be a feature of any model in which accumulation of human capital is the main use of time (and other resources) alternative to the production of physical goods (e.g. Lucas (1988)). Given the widespread use of those models in the endogenous growth literature, we choose to devote the next section to assessing their potential as an explanation for our results.

b) Testing the "Human Capital" Hypothesis

One way to test the "human capital" hypothesis is to look for direct evidence for a countercyclical pattern in human capital investment, either through formal education or job training. Except perhaps for professional schools, there is no clear evidence that investment in formal education is markedly cyclical. The following regressions illustrate this point. We regress the enrollment rate for ages 20-24 (*"SC2024"*, U.S. Department of Education (1989)) on the NBER business cycle trough dummy (*"TROUGH"*) and on the unemployment rate (*"UNEM"*):

$$sc2024 = const. + \underset{(0.02)}{0.42}\, TIME - \underset{(0.81)}{0.66}\, TROUGH - \underset{(0.80)}{1.08}\, TROUGH_{-1}$$

$$sc2024 = const. + \underset{(0.02)}{0.44}\, TIME - \underset{(0.24)}{0.43}\, UNEM - \underset{(0.28)}{0.23}\, UNEM_{-1}$$

In both regressions, coefficients are insignificant and of the "wrong" sign[25].

If we turn to job training, however, we do find evidence of a somewhat countercyclical pattern. Using *National Longitudinal Survey* data for the period 1966 to 1981 Lillard and Tan (1986) find that "for mature men and career women, periods of high national unemployment are associated with a greater likelihood of training from company sources, especially professional and technical types of training, while no significant effects are found for young men" (p. 39). They also point out that "one possible interpretation is that employers are more likely to retrain older workers during periods of slack economic activity when the opportunity cost of

[25] In independent work, Dellas (1993) estimates a number of related regressions, including panel data regressions using state data. His results provide more encouraging evidence for the human capital hypothesis.

their time is low" (p. 39). Survey evidence by Fay and Medoff (1985) confirms this interpretation. Plant managers were asked whether they assigned any work other than regular production tasks during the trough quarter of their most recent completed downturn. Of the 168 respondents, 78 did not assign any such tasks. But of the 90 who did, 34% assigned training tasks.

Though this kind of direct evidence is suggestive of the potential role of job training in providing a link between economic fluctuations and aggregate productivity changes, it obviously cannot provide an answer as to whether job training is a *significant* factor underlying our results. More systematic research, conditional on availability of relevant aggregate data, would have to be undertaken in order to assess the role of job training as a "transmission mechanism."

An alternative, less direct way of testing the "human capital" hypothesis is to construct a *quality adjusted* measure of the labor and the Solow residual, and estimate a VAR model identical to the one above using this alternative data set. We follow this strategy below, using the time series for quality adjusted labor and capital inputs found in Jorgenson, Gollop and Fraumeni (1987). The resulting measures of productivity growth will thus be *net* of changes in productivity embodied in inputs. Naturally, the test's validity depends on the extent to which the quality adjustment procedure used reflects the actual quality of inputs.

The construction method for the quality adjusted series we use is quite simple. Consider an economy in which there exist J different labor qualities available, indexed by $j = 1,2,...J$. In the simplest case, the aggregate production function is given by

(8) $$Y_t = A_t\, F(L_t\,, K_t\,),$$

where Y, L, and K are aggregate measures of output, labor, and capital, and A is "disembodied productivity". Assume that L is a composite index defined by

(9) $$L_t \equiv exp\,\{\sum_{j=1}^{J} \omega_j\, L_t^j\,\},$$

where $\sum_{j=1}^{J} \omega_j = 1$. In that case the growth rate of effective or quality adjusted labor input is given by $\Delta l_t = \sum_{j=1}^{J} \omega_j\, \Delta l_t^j$, where, like before, lower case letters denote natural logarithms. It is easy to show that the weights ω_j can be recovered, given information on the relative shares of different labor types in aggregate labor input, so Δl can be easily computed given appropriate data. A similar approach can be taken in order to compute quality adjusted measures of capital input (see Jorgenson et al. (1987) for details).

Clearly, changes in the aggregate quality adjusted measures of each input will have two components: (i) changes in quantities (e.g. total hours), and (ii) changes in the distribution of a given quantity across qualities. To the extent that endogenous productivity growth takes the form of changes in the latter distribution, changes in labor-embodied and capital-embodied productivity will be reflected in the quality adjusted measure of each input.

New measures of productivity growth (net of changes in the quality of inputs) can be computed using the formulas above, after replacing the standard input measures by the quality adjusted measures constructed by Jorgenson et al. (1987). The latter are available yearly for the sample period 1948-1979 only, so the analysis is restricted to that period and frequency.

Table 3 reports the results of Granger causality tests using the new productivity measures, and either *N(er)* or *N(cu)* as a cyclical indicator. Despite the relatively short sample, Granger causality is established in all cases at conventional significance levels.

Figure 5 contains the estimated impulse responses of productivity and employment, using the standard Solow residual (computed with the Jorgenson et al. data set) as a measure of productivity growth. Qualitatively, the emerging picture is not different from that found in Figure 2. Similar results obtain when we modify the productivity variable in order to account for labor hoarding or increasing returns and market power.

Overall, the above results suggest that some mechanism other than changes in the distribution of quality of inputs must underlie the dynamic response of productivity to demand shocks estimated at the beginning of section 3. Otherwise, the initial results (including both the Granger causality tests and the impulse responses) would not obtain again when we use the quality adjusted input measures. Thus, an explanation for the results of this paper will need to

be based on changes in aggregate disembodied productivity or, alternatively, changes in the overall quality of inputs that do not alter the distribution of qualities. Further evidence, as well as more theoretical models consistent with the evidence presented in this paper, will have to be brought into play in order to make additional progress in elucidating the nature of the interaction between productivity growth and economic fluctuations.

5. Summary and Conclusions

In this paper we have examined three different hypotheses concerning the interaction between economic fluctuations and productivity growth. After developing a simple theoretical framework capable of embedding those hypotheses, we used a VAR model to assess their empirical relevance. Both the theoretical model and the corresponding VAR allow for two sources of economic fluctuations: technology shocks and demand shocks. In a way consistent with the prediction of real business cycle models, our estimates suggest that positive technology shocks generate a temporary increase in employment, and raise the level of productivity permanently. On the other hand, positive demand shocks that increase employment temporarily tend to reduce productivity in the long run. Those results are robust to the use of alternative productivity and business cycle measures. They are also unchanged when we use productivity measures computed on the basis of quality-adjusted inputs. The estimated model yields an interpretation of historical U.S. business cycles that is consistent with traditional views. Further sectoral and international evidence concerning our findings are a natural extension for this line of research.

A number of interpretations of the negative effect of demand shocks on productivity were discussed, including "cleansing" and "opportunity cost" explanations.

Given the spectrum of possible interpretations and their compatibility with very different views of the macroeconomy, great care should be taken not to infer unwarranted welfare or policy conclusions from our findings. Although the notion that demand-induced recessions are beneficial for productivity points to one benefit of recessions, it does not necessarily imply that "recessions are desirable". In some models (e.g., a version of the model in section 2 without external learning by doing effects) recessions—and economic fluctuations in general—are optimal responses to aggregate shocks, and no case can be made for activist policies. Perhaps in models with market imperfections or coordination failures, recessions could be highly inefficient responses to those shocks, and that inefficiency may outweigh any benefits from improved productivity.

Appendix 1

This appendix discusses technical details of the identification and estimation procedures used in section 3. It also shows the relationship in our empirical model between Granger causality and the exogenous productivity hypothesis.

Specification.

Consider the Wald moving average representation of $\{[\Delta s'_t, N'_t]\}$, given by

$$\begin{bmatrix} \Delta s'_t \\ N'_t \end{bmatrix} = \begin{bmatrix} E_{11}(L) & E_{12}(L) \\ E_{21}(L) & E_{22}(L) \end{bmatrix} \begin{bmatrix} \nu_{s,t} \\ \nu_{n,t} \end{bmatrix} \equiv E(L)\, \nu_t$$

where $E(0) = I$, and

$$\nu_{s,t} \equiv \Delta s'_t - P[\Delta s'_t | \Delta s'_{t-1}, N'_{t-1}, \Delta s'_{t-2}, N'_{t-2}, \ldots],$$
$$\nu_{n,t} \equiv N'_t - P[N'_t | \Delta s'_{t-1}, N'_{t-1}, \Delta s'_{t-2}, N'_{t-2}, \ldots],$$

i.e. ν_t is the vector of residuals from the projection of $[\Delta s'_t, N'_t]$ on its own lags. Let Σ denote the variance-covariance matrix of ν.

Note that if s was I(0) (possibly around a deterministic trend), $|E(z)|$ would vanish for z=1 and the moving average representation of $[\Delta s_t, N_t]$ would not be invertible. Since our estimation procedure is based on a (truncated) VAR representation, we need to assume s is an I(1) process. It is easy to show that the model in section 2 has such a finite-order VAR representation.

We assume that innovations to each variable are linear combinations of the contemporaneous fundamental shocks, i.e. $\nu_t = Q\, \varepsilon_t$, all t, for a unique non-singular Q. Clearly, $QQ' = \Sigma$.

Given the Wald representation above, it follows that $C(L)$ in (7) can be expressed as $C(L) = E(L)\, Q$. The identifying restriction $C_{12}(0) = 0$, together with $E(0)$=I, implies that Q is lower triangular, and can thus be uniquely determined (up to column sign) from the Choleski factorization of Σ. Since an estimate of $E(L)$ can be obtained by inverting the usual OLS estimate of the reduced form VAR for $[\Delta s, N]$, the knowledge of Q allows us to recover an estimate of $C(L)$.

Granger-causality.

Under the hypothesis of exogenous productivity both $C(L)$ and Q are lower-triangular. Since $E(L) = C(L)\ Q^{-1}$, $E(L)$ will also be lower triangular. In that case, the reduced-form VAR representation of $(\Delta s'_t, N'_t)$ takes the form:

$$\begin{bmatrix} B_{11}(L) & 0 \\ B_{21}(L) & B_{22}(L) \end{bmatrix} \begin{bmatrix} \Delta s'_t \\ N'_t \end{bmatrix} = \begin{bmatrix} v_{s,t} \\ v_{n,t} \end{bmatrix}$$

where $B_{11}(L) = E_{11}(L)^{-1}$, $B_{21}(L) = -E_{22}(L)^{-1}E_{21}(L)E_{11}(L)^{-1}$, and $B_{22}(L) = E_{22}(L)^{-1}$. Clearly, n does *not* Granger-cause Δs in this case. Such lack of Granger-causality is thus a necessary condition for exogenous productivity. Conversely, assume that N' does not Granger-cause $\Delta s'$. Then $E(L)$ is lower triangular, and so is $C(L)$, given $C(L)=E(L)\ Q$ and Q lower triangular. Thus, given a lower triangular Q, lack of Granger causality from N to Δs implies that productivity is exogenous.

Appendix 2

This appendix derives the three productivity measures used in section 2. The "representative" firm's production function is

$$Y_t = S_t\ F(K_t, H_t),$$

where S is total factor productivity and Y, K and H are output, capital and hours. Letting lower-case variables denote *logs*, we have:

$$\Delta s_t = \Delta y_t - [\ \phi^h_t\ \Delta h_t + \phi^k_t\ \Delta k_t\ ]$$

where ϕ^x denotes the elasticity of output with respect to input x. We consider three cases.

Case 1: Standard. The "standard" case assumes constant returns, perfect competition, and no measurement problems. It follows that $\phi^h + \phi^k = 1$, and ϕ^h equals the (observable) labor share of income α_t. In this case, productivity growth is measured by the standanrd "Solow residual" (Solow (1957)):

$$\Delta s_t = \Delta y_t - [\ \alpha_t\ \Delta h_t + (1-\alpha_t)\ \Delta k_t\ ].$$

Case 2: Labor Hoarding. In this case, we retain the "standard" assumptions above, but introduce a measurement problem. Under the labor hoarding hypothesis changes in measured hours tend to understate effective changes in labor input, because of a procyclical rate of utilization of that input. We follow Gordon (1990) and write $H^*_t = E_t\ H_t$, where H^* and H denote *effective* and *measured* labor input and E is the rate of labor input utilization. We assume E to be stationary around one, and define $e_t \equiv log\ E_t$. Let $\hat{H}^*_t$ and $\hat{H}_t$ be stationary percent deviations of H^*_t and H_t from an exogenous trend. It follows that $\hat{H}^*_t = e_t + \hat{H}_t$. As in Gordon (1991) we assume that a fraction φ of changes in the effective $\hat{H}^*_t$ takes the form of changes the labor utilization rate. Formally, $e_t = \varphi\ \hat{H}^*_t$, thus implying $e_t = [\varphi/(1-\varphi)]\ \hat{H}_t$. The growth rate in effective hours is therefore $\Delta h^*_t = \Delta h + [\varphi/(1-\varphi)]\ \Delta\hat{H}_t$.

Given φ, growth in multifactor productivity can thus be measured as follows:

$$\Delta s_t = \Delta y_t - [\, \alpha_t \, \Delta h_t^{*} + (1-\alpha_t)\, \Delta k_t \,]$$
$$= \Delta y_t - [\alpha_t \Delta h_t + (1-\alpha_t)\Delta k_t] - [\varphi/(1-\varphi)]\alpha_t \Delta \hat{H}_t$$

Case 3: IRS-Market Power. This last case assumes F is homogeneous of degree γ, so $\phi^h + \phi^k = \gamma$. It also assumes a constant markup μ of price over marginal cost. As shown in Hall (1990), $\phi_t^h = \mu\alpha_t$ holds in this case. It follows that productivity growth can be measured by

$$\Delta s_t \equiv \Delta y_t - \gamma \, \{ \, (\mu/\gamma)\alpha_t \Delta h_t + [1-(\mu/\gamma)\alpha_t] \, \Delta k_t \, \}$$

Moreover, it can be shown that the ratio μ/γ must lie between 1 and $1/\alpha_t$. The lower bound of 1 follows immediately from the second order conditions for profit maximization. The upper bound follows from the fact that $[1-(\mu/\gamma)\alpha_t]$ measures the cost share of capital (Hall (1990) and must therefore be non-negative.

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TABLE 1 : Unit Root Tests

Variable	*Postwar (Quarterly)*	*Full Sample (Yearly)*
Standard		
S	-2.54	-1.95
ΔS	-7.89*	-8.12*
Labor Hoarding		
S	-2.51	-2.16
ΔS	-8.27*	-6.80*
IRS-Market Power		
S	-2.39	-1.69
ΔS	-8.45*	-8.33*
Cyclical Indicators		
$N(er)$	-4.72*	-3.61*
$N(cu)$	-5.10*	-

Note: t statistics on α in the Augmented Dickey-Fuller regression $\Delta x_t = \mu + \beta t + \alpha x_t + \gamma \Delta x_{t-1} + u_t$. The asymptotic 5 and 10 percent critical values for the unit root null are -3.41 and -3.12, respectively. An asterisk denotes rejection of the unit root null at the 5 percent level.

Table 2 : Granger Causality Tests

	Postwar (Quarterly)		*Full Sample (Yearly)*	
	1 lag	*4 lags*	*1 lag*	*4 lags*
Standard				
$N(er)$	0.0003	0.0048	0.0361	0.1444
$N(cu)$	0.0001	0.0040	-	-
Labor Hoarding				
$N(er)$	0.0004	0.0133	0.0736	0.4534
$N(cu)$	<0.0001	0.0083	-	-
IRS-Market Power				
$N(er)$	0.0004	0.0109	0.0443	0.3439
$N(cu)$	0.0001	0.0065	-	-

Note: For each measure of N and ΔS the table reports the joint significance level of the coefficients of $\beta(L)$ in the regression $\Delta S_t = \mu + \alpha(L)\Delta S_{t-1} + \beta(L)N_{t-1}$.

Table 3 : Granger Causality Tests with Quality Adjusted Data

	1 lag	*4 lags*
Standard		
N(er)	<0.0001	0.0259
N(cu)	0.0001	0.0014
Labor Hoarding		
N(er)	0.0015	0.0365
N(cu)	0.0002	0.0079
IRS-Market Power		
N(er)	0.0003	0.0336
N(cu)	<0.0001	0.0032

Note: For each measure of N and ΔS the table reports the joint significance level of the coefficients of $\beta(L)$ in the regression $\Delta S_t = \mu + \alpha(L)\Delta S_{t-1} + \beta(L)N_{t-1}$.

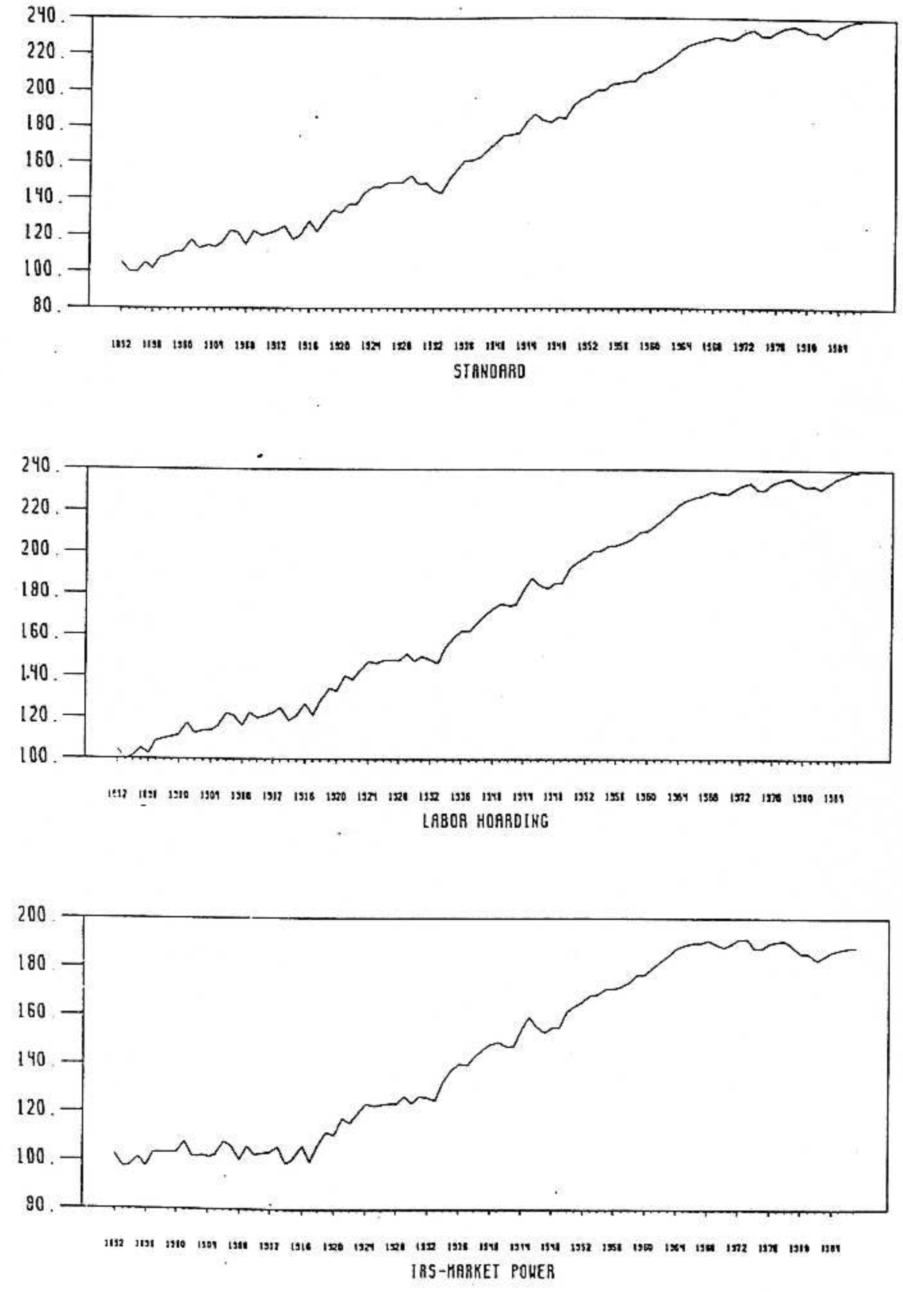

Figure 1

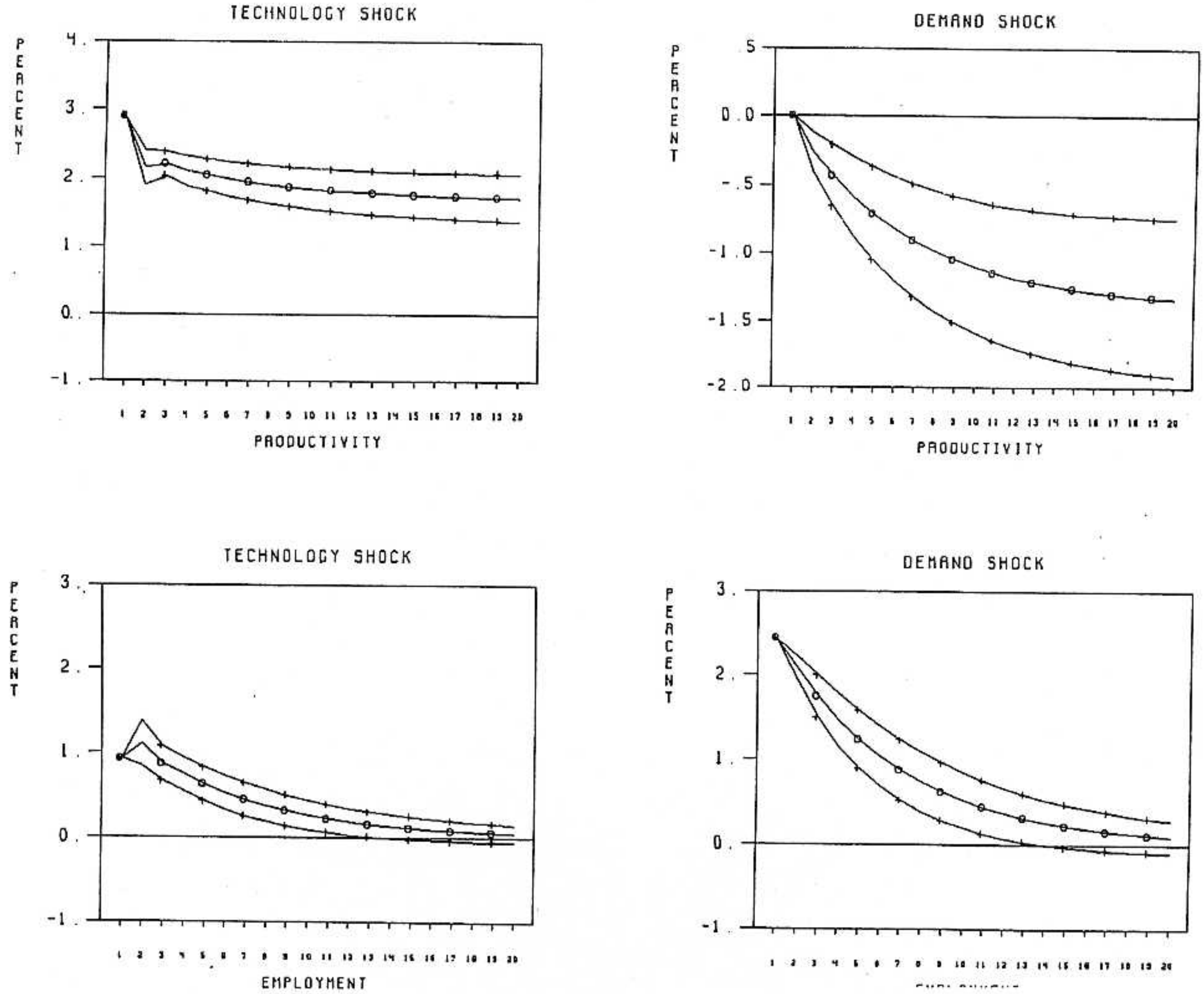

Figure 2b

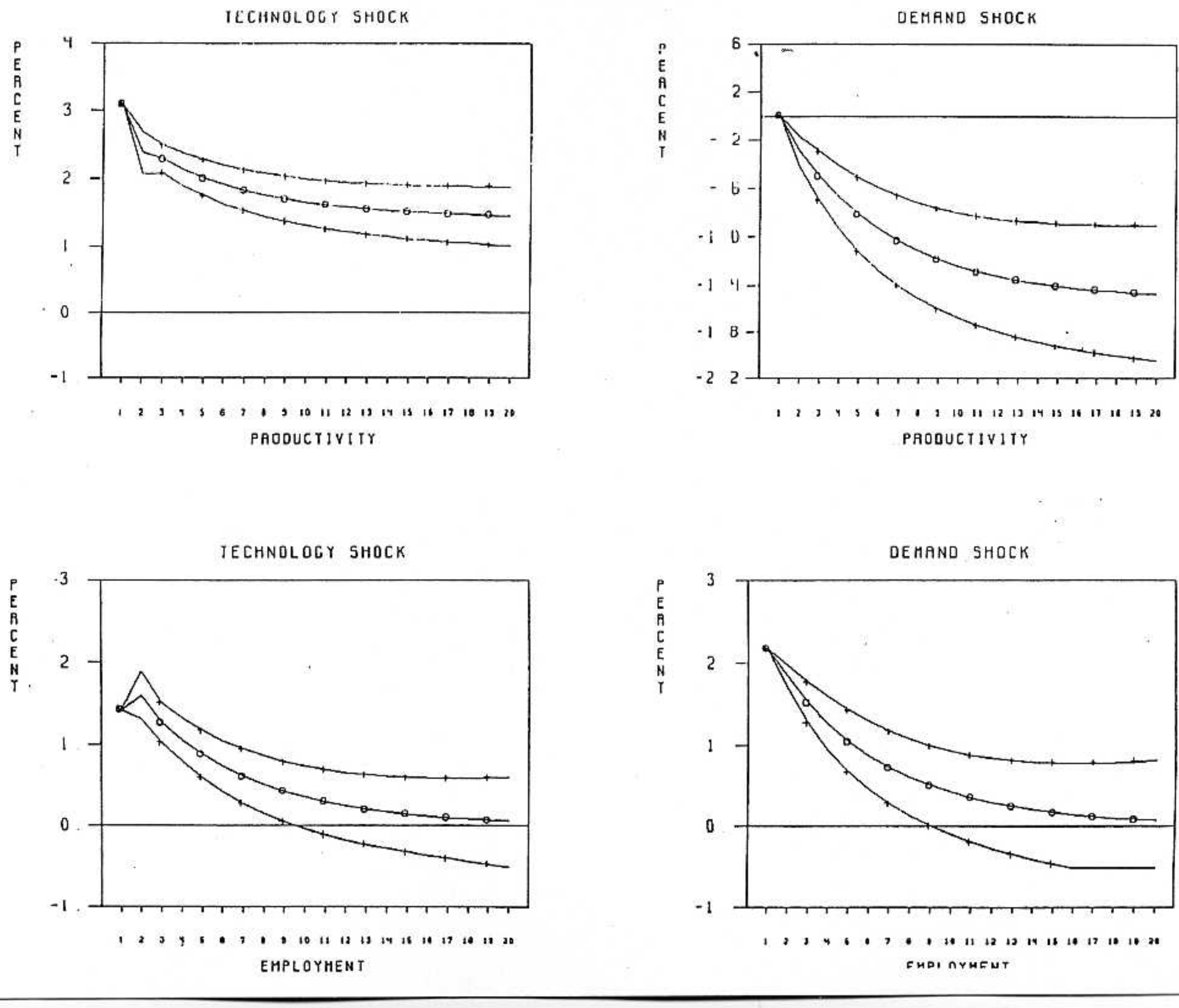

Figure 2a

Figure 3b

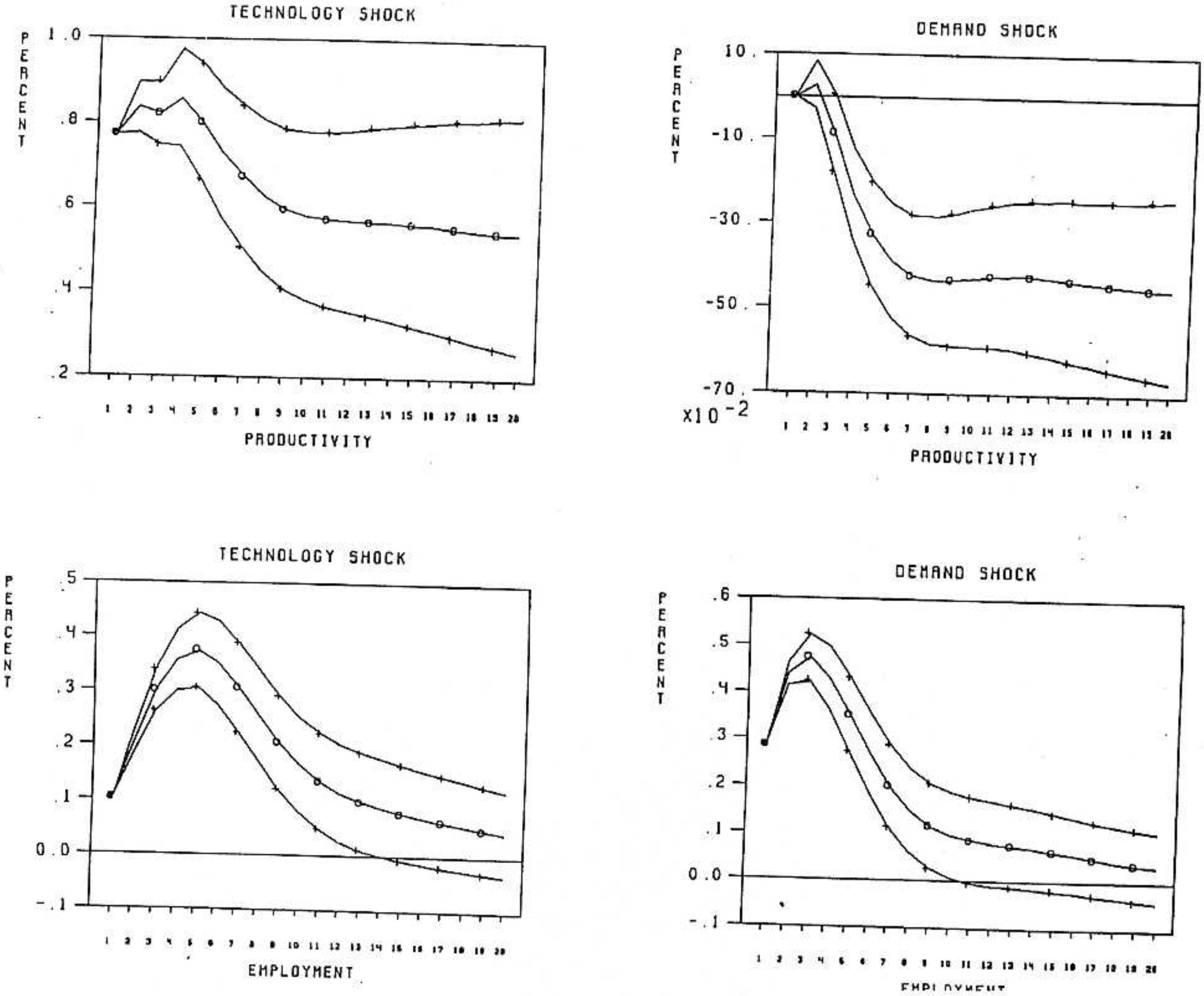

Figure 3a

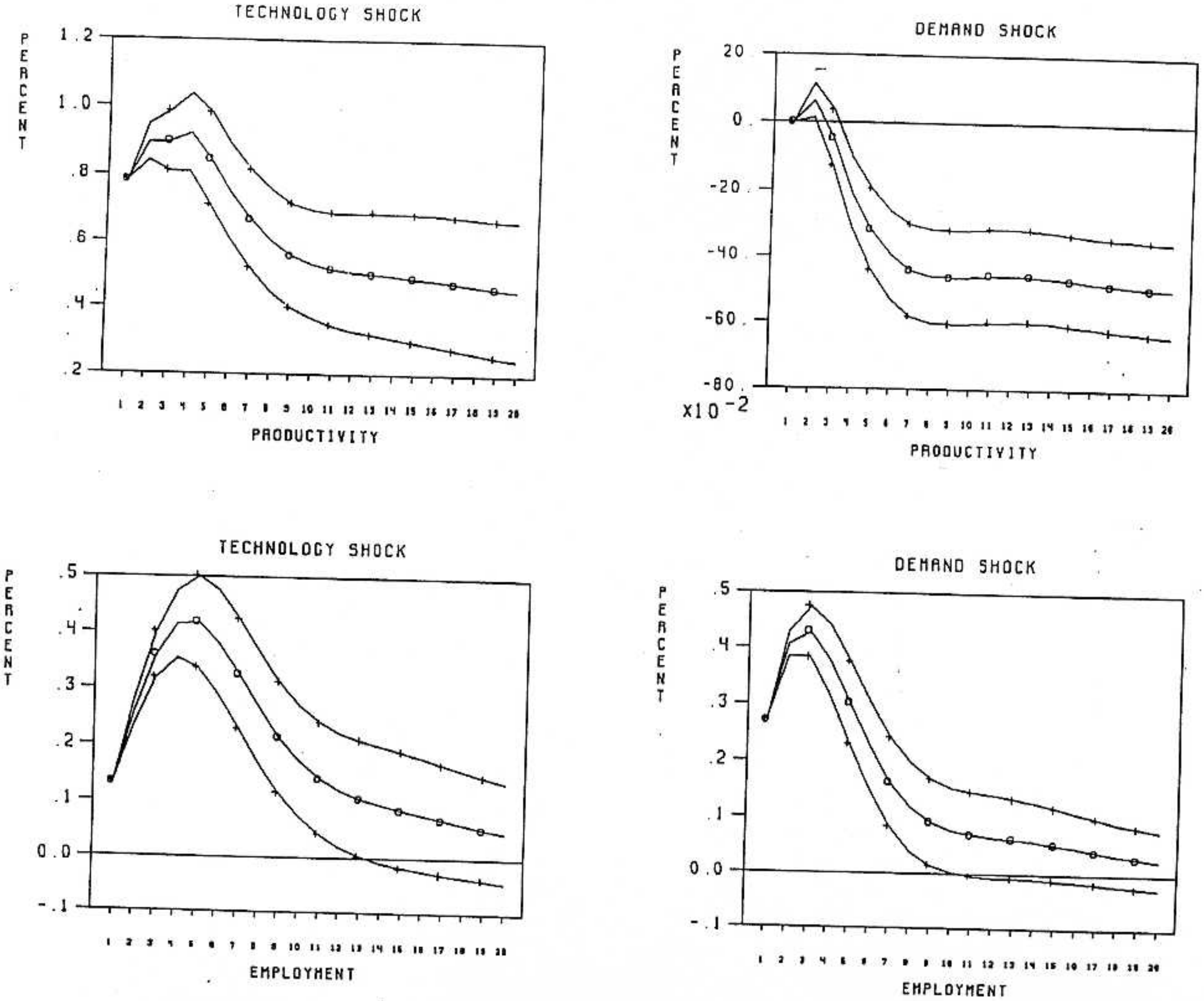

Figure 4b

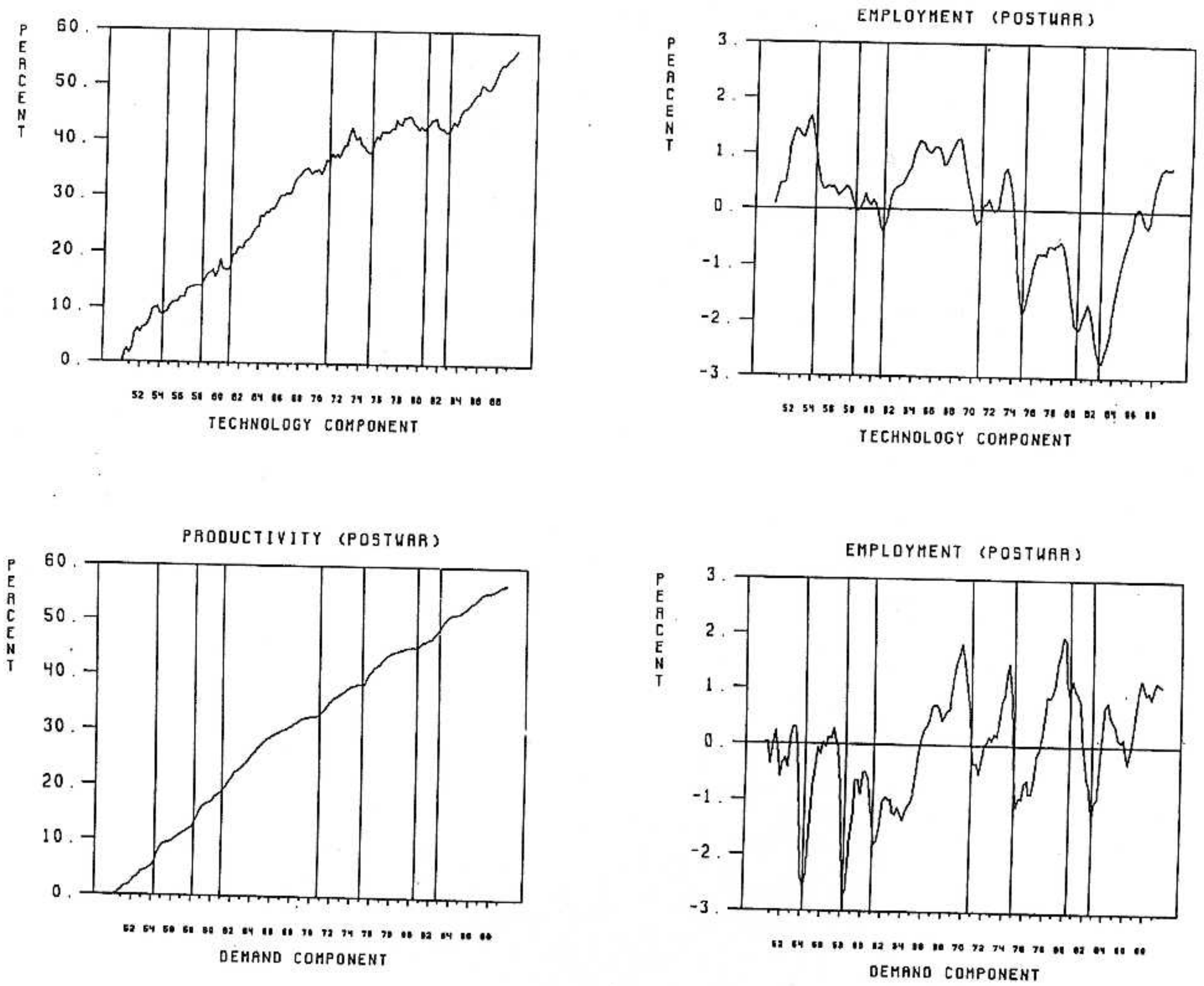

Figure 4a