

# Unraveling Trend and Stationary Components of Total Factor Productivity

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**ABSTRACT.** – We propose a methodology to analyze the dynamic features of total factor productivity (TFP). Factor efficiency is assumed to evolve according to an unobserved component model which has the form of a dynamic version of factor analysis and which nests most of the specifications for technology shocks used in the literature. We show under which conditions the processes generating the components can be identified from measurements of TFP only. We also discuss how additional information on the technology shocks can be obtained from the factor demand equations associated with the production technology.

The methodology is applied to quarterly data for the manufacturing industry in the Netherlands 1971.I-1990.IV. Technology is found to be driven by a stochastic trend with a first order moving average part. This finding is similar to results obtained by LIPPI and REICHLIN (1994) among others; The findings for TFP corroborate earlier findings for the dynamic features of technology in labor and capital demand equations for the manufacturing industry in the Netherlands.

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## Décomposition en tendance et composantes stationnaires de la productivité totale des facteurs

**RÉSUMÉ.** – Nous proposons une méthodologie pour l'analyse des caractéristiques dynamiques de la productivité totale des facteurs de productions.

Nous supposons que l'évolution de l'efficacité des facteurs est engendrée par un modèle à composantes non-observables qui prend la forme d'une version dynamique d'un modèle à facteurs et qui englobe la majorité des spécifications des chocs technologiques utilisés dans la littérature.

Nous montrons sous quelles conditions il est possible d'identifier les processus qui engendrent les composantes en se basant uniquement sur les mesures de la productivité totale des facteurs.

Nous montrons également comment les équations de demande de facteurs associées à la technologie de production peuvent fournir de l'information additionnelle concernant les chocs technologiques.

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# 1 Introduction

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Most research on the productivity growth is done along the lines of SOLOW [1957]. To measure the effect of Hicks neutral technological change, one can subtract a Divisia index of input growths from output growths to obtain the SOLOW residual, an index of total factor productivity (TFP), that measures the accumulated effect of technology shocks. In real business cycle models, the variability of the SOLOW-residual is considered as a good proxy for the variability of exogenous technology shocks that drive the economy's cyclical behavior (KYDLAND and PRESCOTT, 1982). Moreover, if growth is assumed to originate from technology shocks, all trending variables in the economy should share the same trend representing the accumulated nonstationary TFP. For example, in earlier work on manufacturing factor demand in the Netherlands, the U.K. and the U.S. we found that factor input, relative factor prices and TFP are cointegrated with labor and capital respectively <sup>1</sup>.

Alternatively, technology shocks can be interpreted as Marshallian productive externalities that give rise to increasing returns to scale (*see e.g. CABALLERO and LYONS, 1990*). In theory, plausible modifications of technology shock-driven as well as increasing returns economies can produce similar characteristics of macroeconomic variables (MURPHY, SHLEIFER and VISHNY, 1989). BLANCHARD and QUAH [1989] identify permanent and transitory shocks from the joint dynamic processes of output and unemployment as technology and demand shocks respectively. Much of the recent debate in the econometric literature has been concerned with questions whether technological change is nonstationary and if it is, whether it should be modeled as a deterministic or a stochastic trend and whether one should allow for serial correlation in addition to a deterministic or stochastic trend. In the literature on industrial organization, to address questions about the internal or external nature of returns to scale, the impact of technology shocks on production has to be appropriately measured and modeled.

In this paper, the starting point is a continuous production function with two factors of production, labor and capital, and a stochastic component. This simple specification is chosen to illustrate how and when we can identify the parameters of the stationary and nonstationary processes that characterize factor efficiency. TFP is assumed to consist of an economy wide nonstationary part, and idiosyncratic stationary components of capital and labor efficiencies. The methodology developed in this paper can be applied to all types of continuous production functions for which a consistent estimate of TFP can be obtained. Here it is applied to quarterly data for the Netherlands manufacturing sector, 1971.I – 1990.IV.

The plan of the paper is as follows. In Sections 2 and 3, the theoretical framework is presented, the identification of the time-series properties of the nonstationary component of TFP is examined and illustrated with an empiri-

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1. *See* KODDE, PALM and PFANN (1990), PEETERS, PALM and PFANN (1993), and PFANN and PALM (1993).

cal example. In Section 4 and 5 we explain that additional information, that can be obtained from first order necessary conditions for intertemporal profit maximization, is necessary to identify the bivariate stationary process of the serially correlated labor and capital efficiencies. We find that the volatility of the stationary components of TFP exceeds that of the trend component by an average factor of ten. The drift parameter plays an important role in the factor demand equations. The non-stationarity of labor and capital is, just like TFP, a combination of a unit root and a trend component. Moreover, the variance of stationary shocks in employment exceeds that of capital, which is conform the stylized fact that capital is a more “fixed” (in the terms of Oi, 1962) factor of production than employment.

## 2 Modeling Total Factor Productivity

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To establish a basis for assessing the impact of technological change on production possibilities, one needs an analytically meaningful way of accounting for the growth at the level of the production unit. Consider a firm operating at any moment of time using a continuous production function which reads as follows

$$(1) \quad Y_t = F(L_t, K_t, E_{1t}, E_{2t}),$$

where  $Y_t$ ,  $L_t$ , and  $K_t$  denote respectively production, labor and capital and  $E_{1t}$  and  $E_{2t}$  represent the efficiencies of labor and capital respectively. Furthermore, we assume  $F$  is homogeneous of degree  $\gamma_t$  in  $L_t$  and  $K_t$ . The total differential of  $y = \ln Y$  can be written as

$$(2) \quad dy_t = \alpha_t dl_t + \beta_t dk_t + \delta_{1t} dz_{1t} + \delta_{2t} dz_{2t},$$

where we use the notation  $\alpha_t = F_L L/Y$  and  $\beta_t = F_K K/Y$ ,  $\delta_{1t} = F_1 E_1/Y$  and  $F_2 E_2/Y$  with  $F_x = \partial F/\partial X$ ,  $l_t = \ln L_t$ ,  $k_t = \ln K_t$ ,  $z_{it} = \ln E_{it}$ . When the arguments of the production function (1) are  $L_t E_{1t}$  and  $K_t E_{2t}$ , the restrictions  $\alpha_t = \delta_{1t}$  and  $\beta_t = \delta_{2t}$  hold.

The random shocks  $z_{it}$  are assumed to have the following structure

$$(3a) \quad z_{it} = \mu_t + (1 - \rho_i L)^{-1} \varepsilon_{it}, \quad \varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})' \sim N(0, \Sigma)$$

with

$$(3b) \quad \mu_t = \tau + \mu_{t-1} + \eta_t, \quad \eta_t \sim N(0, \sigma_\eta^2),$$

where  $\mu_t$  is generated by a random walk with common variance  $\sigma_\eta^2$  and common drift parameter  $\tau$  and  $\varepsilon_{it}$  denotes the idiosyncratic component of factor  $i$ ,  $|\rho_i| < 1$  and  $L$  is the lag operator. The components  $\eta_t$  and  $\varepsilon_t$  are serially uncorrelated and uncorrelated with each other. We shall allow  $\varepsilon_{1t}$  and  $\varepsilon_{2t}$  to be correlated.

The unobserved component specification (3) has been chosen such that many of the processes used in the literature to model total factor productivity (TFP) are nested in it. For instance when  $\sigma_1^2 = \sigma_2^2 = \sigma_\eta^2 = 0$ , TFP can be represented by a linear deterministic trend with slope coefficient  $\tau$ . For instance, DAVID and VAN de KLUNDERT [1965] included a deterministic trend in a CES production function in order to measure the impact of technological change on factor efficiencies. If  $\tau = 0$  and  $\sigma_1^2 = \sigma_2^2 = 0$ , TFP is generated by a random walk without drift, a model which is in line with that put forward by e.g. LIPPI and REICHLIN [1994]. A stationary AR(1) process with  $\rho$  less than but near one has been used by KYDLAND and PRESCOTT [1982] to model the persistence of the permanent component of the technology shock while the transitory component is white noise. Notice that the variables in their model have been detrended using the HODRICK-PRESCOTT filter so that there is no need to include a nonstationary component in their specification. The specification (3) accounts for a deterministic and/or a stochastic trend as well as for a possible transitory component. For instance if one of the  $\rho_i$ 's is zero, the stationary part is the white noise  $\varepsilon_{it}$  and is observationally equivalent to a transitory component. Moreover, one can interpret the nonstationary component as reflecting the impact of common persistent innovations on TFP and the stationary component as representing the effects of idiosyncratic incremental innovations. Alternatively, the nonstationary component may reflect the impact of frequent but radical shocks on TFP. This interpretation is related to the notion that growth would die out if there were no radical innovations, a fact recognized in the literature (*see* e.g. FREEMAN [1979]). Radical innovations that arrive infrequently (*cf.* AGHION and HOWITT [1992]) could be captured to model  $\eta_t$  as Poisson arrivals on the drift  $\mu_t$ .

Assume in first instance that the coefficients  $\alpha_t$  and  $\beta_t$  are known and constant, that  $\alpha = \delta_1$  and  $\beta = \delta_2$  and that differentials can be replaced by first differences. Then the first differences,  $\Delta$ , of the so-called SOLOW residual  $u_t$  can be expressed as

$$(4) \quad \Delta u_t = \alpha \Delta z_{1t} + \beta \Delta z_{2t}.$$

An unobserved components structure for the technology shocks has also been proposed by CABALLERO and LYONS [1990]. Note, for instance, that if  $F$  is a COBB-DOUGLAS production function with constant factor elasticities  $\alpha$  and  $\beta$  and with discrete time parameter  $t$

$$(5) \quad \begin{aligned} Y_t &= A_t L_t^\alpha K_t^\beta \\ A_t &= A \exp(\alpha z_{1t} + \beta z_{2t}) = A \exp(u_t), \end{aligned}$$

and  $\Delta \log A_t$  is the SOLOW residual.

Alternatively, the production technology can exhibit increasing returns due to Marshallian productive externalities  $\phi_t$ , considered by MURPHY, SHLEIFER and VISHNY [1989] and CABALLERO and LYONS [1990]

$$\begin{aligned} A_t &= \phi_t \exp(\alpha z_{1t} + \beta z_{2t}) = \phi_t \exp(u_t) \\ \phi_t &= (Y_t^A \exp(-\mu_t))^{\phi_1}, \quad \phi_1 > 0 \end{aligned}$$

where  $Y_t^A$  is the aggregate output (e.g. at the macroeconomic level), so if aggregate economic activity rises relative to the trend the economy as a whole, and consequently the manufacturing sector, become more productive. Here, the increasing returns are a determinant of the rate of technology change and lead to an additional time-dependent component of TFP<sup>2</sup>. Other sources of endogenous growth possibly leading to increasing returns to scale are human capital formation and the resources devoted to R&D. This topic is not pursued any further here as in the empirical part, the assumption of constant returns to scale appears to be appropriate and is made throughout the analysis.

Given  $A_t$  or TFP, a natural question to ask is whether the processes for the components of  $u_t$  can be identified from information on  $u_t$  only. Substituting first differences of (3a) and (3b) into (4) and premultiplying (4) by the lag polynomials in the denominator yields the following result

$$(6) \quad (1 - \rho_1 L)(1 - \rho_2 L) \Delta u_t = (\alpha + \beta)(1 - \rho_1)(1 - \rho_2) \tau \\ + (1 - \rho_1 L)(1 - \rho_2 L)(\alpha + \beta) \eta_t \\ + \alpha(1 - \rho_2 L) \Delta \varepsilon_{1t} + \beta(1 - \rho_1 L) \Delta \varepsilon_{2t}.$$

From expression (6), it becomes obvious that the residual  $u_t$  is generated by an ARIMA(2,1,2) process. This implication which can be checked in a direct way against the information in data on  $u_t$ , follows from the fact that the right-hand side of (6) is a sum of three moving averages of order two. Also, from (6), it follows that the coefficients  $\rho_1$  and  $\rho_2$  are identical to the roots of the autoregressive part. Therefore,  $\rho_1$  and  $\rho_2$  are identifiable from information in the series  $u_t$ . Given that the parameters  $\rho_i$  are identified, the drift parameter  $\tau$  can be obtained from the intercept in the ARIMA model (6). Finally, to identify the variances  $\sigma_\eta^2$ ,  $\sigma_1^2$  and  $\sigma_2^2$  we can use the information on the variance and the first and second order covariances of the moving average (MA) part of (6) denoted by  $w_t$

$$(7a) \quad w_t = (1 - \rho_1 L)(1 - \rho_2 L)(\alpha + \beta) \eta_t + \alpha(1 - \rho_2 L) \Delta \varepsilon_{1t} \\ + \beta(1 - \rho_1 L) \Delta \varepsilon_{2t},$$

which can be reparameterized as

$$(7b) \quad w_t = (1 - \theta_1 L - \theta_2 L^2) v_t,$$

where  $v_t$  is a white noise with expectation zero and constant variance  $\sigma_v^2$ . The relationships between the parameters of the MA part (7b) and the

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2. We find that  $\ln A = \frac{1}{T} \sum_{t=1}^T \ln(\phi_t) = \frac{1}{T} \sum_{t=1}^T \phi_1 (\ln Y_t^A - \mu_t)$ , where  $T$  is the sample size.

parameters of interest  $\sigma_\eta^2$ ,  $\sigma_1^2$  and  $\sigma_2^2$  are

$$\begin{aligned}
(8a) \quad E[w_t^2] &= (1 + \theta_1^2 + \theta_2^2)(\alpha + \beta)^2 \sigma_v^2 \\
&= (1 + (\rho_1 + \rho_2)^2 + (\rho_1 \rho_2)^2) \sigma_\eta^2 \\
&\quad + 2\alpha^2 (1 + \rho_2 + \rho_2^2) \sigma_1^2 + 2\beta^2 (1 + \rho_1 + \rho_1^2) \sigma_2^2 \\
&\quad + 2\alpha\beta (\rho_1 + \rho_2 + 2(1 + \rho_1 \rho_2)) \sigma_{12}.
\end{aligned}$$

$$\begin{aligned}
(8b) \quad E[w_t w_{t-1}] &= \theta_1 (\theta_2 - 1) (\alpha + \beta)^2 \sigma_v^2 \\
&= -(\rho_1 + \rho_2) (1 + \rho_1 \rho_2) \sigma_\eta^2 \\
&\quad + \alpha^2 (1 + \rho_2)^2 \sigma_1^2 - \beta^2 (1 + \rho_1)^2 \sigma_2^2 \\
&\quad - 2\alpha\beta (1 + \rho_1 + \rho_2 + \rho_1 \rho_2) \sigma_{12}.
\end{aligned}$$

$$\begin{aligned}
(8c) \quad E[w_t w_{t-2}] &= -\theta_2 \sigma_v^2 = \rho_1 \rho_2 (\alpha + \beta)^2 \sigma_\eta^2 + \alpha^2 \rho_2 \sigma_1^2 + \beta^2 \rho_1 \sigma_2^2 \\
&\quad + \alpha\beta (\rho_1 + \rho_2) \sigma_{12}.
\end{aligned}$$

Notice that the set of equations (8) is linear in  $\sigma_\eta^2$ ,  $\sigma_1^2$ , and  $\sigma_{12}$ . When  $\sigma_{12} = 0$ , given that  $\alpha$  and  $\beta$  are known (or can be consistently estimated) and that  $\rho_1$  and  $\rho_2$  are identifiable, the system (8) can be solved for  $\sigma_\eta^2$ ,  $\sigma_1^2$ , and  $\sigma_2^2$ , and we conclude that these parameters are identified. If we allowed for contemporaneous correlation between  $\varepsilon_{1t}$  and  $\varepsilon_{2t}$  as in (8), we would have a system of three linear equations in four unknowns  $\sigma_\eta^2$ ,  $\sigma_1^2$ ,  $\sigma_2^2$  and  $\sigma_{12}$ . In that case, the process for the component  $\eta_t$  is identified, but the process for  $(\varepsilon_{1t}, \varepsilon_{2t})$  is not.

Similarly, if the idiosyncratic components are serially correlated, for instance, if they are generated by a first order vector autoregressive (AR) process, the Solow residual becomes

$$(9) \quad u_t = (\alpha + \beta) \mu_t + (\alpha \beta) (I - RL)^{-1} \varepsilon_t,$$

where  $R$  is the matrix of the AR part. First differencing and premultiplying (9) by the determinant of  $(I - RL)$  yields, after substituting expression (3b) for  $\Delta \mu_t$ ,

$$\begin{aligned}
(10) \quad &[(1 - \rho_1 L)(1 - \rho_2 L) - \rho_{12} \rho_{21} L^2] \Delta u_t \\
&= (\alpha + \beta) [(1 - \rho_1)(1 - \rho_2) - \rho_1 \rho_2] \tau \\
&\quad + [\alpha(1 - \rho_2 L) + \beta \rho_{21} L] \Delta \varepsilon_{1t} + [\alpha \rho_{12} L + \beta(1 - \rho_1 L)] \Delta \varepsilon_{2t} \\
&\quad + (\alpha + \beta) [(1 - \rho_1 L)(1 - \rho_2 L) - \rho_{12} \rho_{21} L^2] \eta_t.
\end{aligned}$$

Also in this case, the TFP can be represented by an ARIMA(2,1,2) process. In terms of the order of the process, this case is observationally equivalent to that discussed above with diagonal matrix  $R$ . As is obvious

from the representation (10), the parameters of the matrix R cannot be identified from the AR part. In fact we cannot achieve identification of the processes of the components from information in the series  $u_t$  only. As the variances of the components have to be nonnegative, at most inequality restrictions could be derived for the parameters of interest. Finally, it can be noticed that the specification with more than two uncorrelated first order autoregressive idiosyncratic components is identified.

The implications of these results are far-reaching. First whenever we can get consistent estimates of the Solow residual, we can test for the order of integration using for instance the Dickey-Fuller methodology. Second, we can also empirically determine the order of the univariate process for  $u_t$  or  $\Delta u_t$  if  $u_t$  appears to be integrated of order one. The order can be determined by using the Box-Jenkins approach or by applying a formal consistent model selection criterion.

The outcome of this analysis will either confirm subjective views about the process generating  $u_t$  or give hints about how to revise those prior beliefs. Third, if the component processes are identifiable we can estimate their parameters from the series  $u_t$ . If the parameters of the processes for the components cannot be identified, one will have to bring in additional information to achieve identification. The first order conditions for profit maximization of the firm contain extra information on the technology shocks. This information could be used to achieve identification of the parameters of interest. Notice that the first order conditions for profit maximization could also be used to estimate the parameters of the production function (see e.g. DAVID and VAN de KLUNDERT [1965] and CABALLERO and LYONS [1990]). As the first order conditions of a dynamic optimization problem may be complicated and contrary to a suggestion of CABALLERO and LYONS [1990] may not be well approximated by a sequence of frictionless static problems, the direct approach based on information about TFP is attractive whenever parameter identification is achieved.

### 3 Empirical Analysis of the Nonstationary Component of TFP

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In this section, we apply the methodology to quarterly aggregate data for the manufacturing sector in the Netherlands, 1971.I-1990.IV. A description of the data and their sources are given in an appendix. The data are given in the figures A1 to A6 in the appendix.

Given observations on the labor income share, on output and input growth, along with SOLOW [1957], we can obtain the TFP (the Solow residual) as the rate change of output minus the Divisia index of input growth

$$(11) \quad \frac{\Delta \hat{A}_t}{\hat{A}_t} = \frac{\Delta Y_t}{Y_t} - LIS_t \cdot \frac{\Delta(L_t^* H_t)}{L_t^* H_t} - (1 - LIS_t) \cdot \frac{\Delta(K_t^* U_t)}{K_t^* U_t},$$

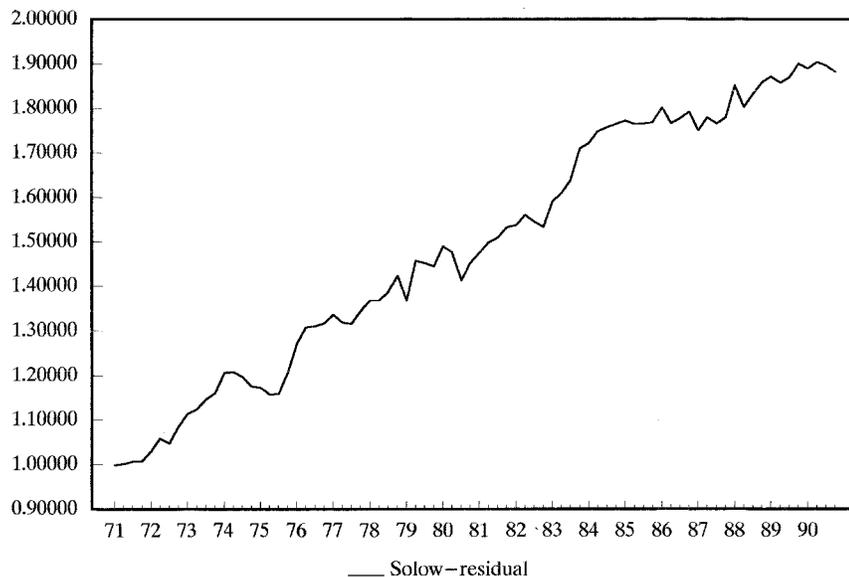
where  $LIS_t$  denotes the labor income share,  $H_t$  denotes paid working time and  $U_t$  is the rate of capital utilization. The absence of reasonably accurate series of user' cost of capital is the empirical basis for ruling out increasing returns. Moreover, due to a lack of reliable data on income shares of other relevant inputs, such as, for example, energy, we estimate the capital income share as  $1 - LIS_t$  (see ROTEMBERG and WOODFORD [1993] for a discussion of this problem). Then, under the maintained assumptions of constant returns to scale and perfect competition, the Solow residual (11) reflects TFP.

Figures 1 and 2 show the Solow residual measured by  $\hat{A}_t$  and the labor income share in the value of total output for the sampling period. The series shown in Figure 1 has been computed using the relationship (11) and setting  $A_0 = 1$ .

FIGURE 1

**Solow Residual.**

Netherlands Manufacturing 1971:1 – 1990:4



Notice that in terms of the Cobb-Douglas specification (5)  $A_t = A \exp(u_t)$  with  $u_t = \alpha z_{1t} + \beta z_{2t}$ , so that  $u_t = \ln A_t - \ln A$ . While the labor income share exhibits a decreasing trend in the second part of the observation period,  $\hat{A}_t$  is subject to a strong positive trend on which fluctuations are imposed. For  $\hat{A}_t$ , the Dickey-Fuller and the augmented Dickey-Fuller statistics are respectively  $-2.781$  [.218] and  $-2.271$  [.491] with  $p$ -values given in square brackets. For  $\ln \hat{A}_t$ , the corresponding values are  $-2.026$  [.637] and  $-1.856$  [.726] respectively. The trend is appropriately accounted for by taking first differences or relative changes of  $\hat{A}_t$ . There is little evidence for the presence of a segmented trend in  $\hat{A}_t$  for the period of time under consideration.

FIGURE 2

*Labor Income Share.*

Netherlands Manufacturing 1971:1 – 1990:4

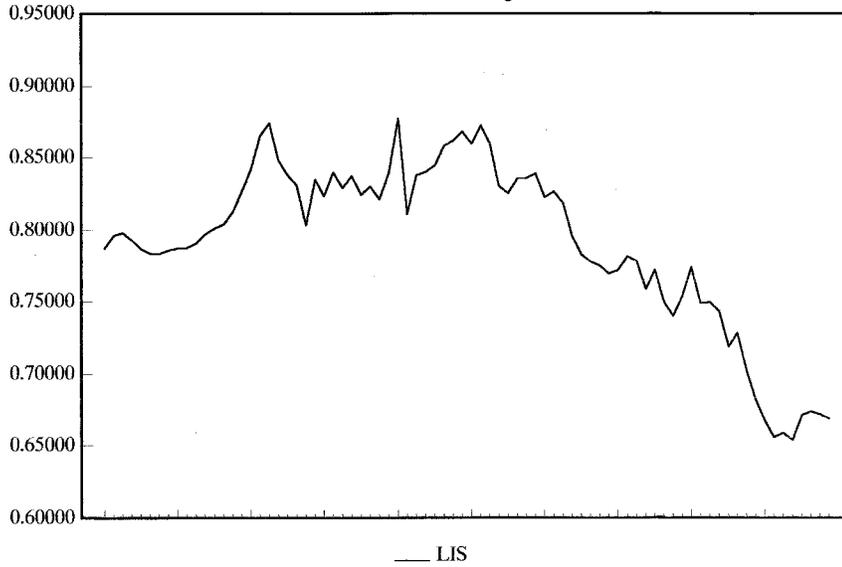


TABLE 1

*Autocorrelations and Partial-Autocorrelations of  $\Delta\hat{A}_t$  and  $(\Delta\hat{A}_t/\hat{A}_t)$ .*

Order	1	2	3	4	5	6	7	8	9	10	
$\Delta\hat{A}_t$	AC	-.192	-.053	.242	-.254	-.113	-.023	-.071	.057	.117	-.071
	S.E.	.113	.117	.117	.123	.130	.131	.131	.131	.132	.133
	PAC	-.192	-.093	.223	-.185	-.186	-.164	-.024	.060	.123	-.089
	S.E.	.112	.112	.112	.112	.112	.112	.112	.112	.112	.112
$\Delta\hat{A}_t/\hat{A}_t$	AC	-.117	-.045	-.208	-.227	-.158	-.027	-.058	.075	.130	-.068
	S.E.	-.113	.114	.114	.119	.124	.127	.127	.127	.128	.129
	PAC	-.117	-.059	.199	-.193	-.199	-.130	-.005	.101	.119	-.106
	S.E.	.113	.113	.113	.113	.113	.113	.113	.113	.113	.113

Next we analyze the time series properties of  $\Delta\hat{A}_t$  and  $\Delta\hat{A}_t/\hat{A}_t$  being estimated from (11). The autocorrelation (AC) and partial autocorrelation (PAC) functions of  $\Delta\hat{A}_t$  and  $\Delta\hat{A}_t/\hat{A}_t$  are given in Table 1, together with their standard errors (S.E.).

The numbers in Table 1 suggest an I(0) or an MA(1) process for  $\Delta\hat{A}_t$  and  $\Delta\hat{A}_t/\hat{A}_t$ . Estimation results for these models and for the more general ARMA(1,1) specification are given in Table 2.

The likelihood ratio statistics, LR, of 3.267 and 1.179 in Table 2 compare the I(0) model with the MA(1) model. In terms of the t-test or the LR-test

TABLE 2

Univariate Models for  $\Delta\hat{A}_t$  and  $\Delta\hat{A}_t/\hat{A}_t$ .<sup>a)</sup>

1. I(0)	$\Delta\hat{A}_t = .01117 + e_t$ (3.360) S.E. = .027350 RSS = .058346	
2. MA(1)	$\Delta\hat{A}_t = .011278 + (1-.206L)e_t$ (4.659) (1.827) S.E. = .026964 RSS = .055982	LR(1) = 3.267 p-value = .071
3. ARMA(1,1)	$(1+.023L)\Delta\hat{A}_t = .011532 + (1-.184L)e_t$ (-.041) (1.709) (.334) S.E. = .027140 RSS = .055980	LR(1) = .0028 p-value = .958
4. I(0)	$\Delta\hat{A}_t/A_t = .00212 + e_t$ (3.769) S.E. = .018863 RSS = .027753	
5. MA(1)	$\Delta\hat{A}_t/A_t = .00804 + (1-.124L)e_t$ (4.321) (1.090) S.E. = .018844 RSS = .027342	LR(1) = 1.179 p-value = .277
6. ARMA(1,1)	$(1-.747L)\Delta\hat{A}_t/A_t = .00206 + (1-.851L)e_t$ (2.738) (.945) (3.880) S.E. = .018894 RSS = .027132	LR(1) = .609 p-value = .435

<sup>a)</sup> t-values are given between parentheses.

for the MA parameter, the MA(1) model is preferred to the pure I(0) model for  $\hat{A}_t$ . Also in terms of fit, the former model is the preferred one. For the ARMA(1,1) model, none of the parameters of the lagged variables is significant. The results in Table 2 suggest that  $\hat{A}_t$  could be modeled as an MA(1) process. For  $\Delta\hat{A}_t/\hat{A}_t$ , the MA(1) model is not preferred to the I(0) model on statistical grounds although there is some first order serial in the series. In the ARMA(1,1) model there appear to be two common factors which cancel against each other and yield a model which is close to the MA(1) model. Note that the constant term  $\hat{\tau}$  is always significantly different from zero, but so close to zero that it will hardly be picked up by statistical tests for unit roots. However, it is just  $\hat{\tau}$  that is responsible for the deterministic trend in TFP.

Table 3 reports the Box-Pierce statistic and its p-value for the residuals of both series. In the first column, the number of residual autocorrelations included in the test statistic is given. From these results, it can be concluded that the I(0) model exhibits some residual serial correlation for high order lags. For the MA(1) and the ARMA(1,1) models, no significant residual autocorrelation is found. From these findings, it can be concluded that the

TABLE 3

**Box-Pierce Test.**

Variable $\Delta \hat{A}_t$ Lag	I(0)		MA(1)		ARMA(1,1)	
	BP	p-value	BP	p-value	BP	p-value
1	3.024	.082	.000	1.000	.000	1.000
2	3.258	.196	.028	.986	.037	.982
3	8.177	.042	3.011	.389	3.010	.390
4	13.676	.008	8.497	.075	8.482	.075
8	15.574	.049	12.504	.130	12.524	.129
12	24.614	.016	18.944	.090	18.981	.089
16	34.942	.004	26.191	.051	26.202	.051
20	41.251	.003	31.541	.048	31.571	.048

Variable $\Delta \hat{A}_t / \hat{A}_t$ Lag	I(0)		MA(1)		ARMA(1,1)	
	BP	p-value	BP	p-value	BP	p-value
1	1.125	.289	.000	1.000	.082	.774
2	1.289	.525	.047	.976	.101	.951
3	4.948	.176	2.692	.441	4.519	.211
4	9.361	.052	7.212	.125	7.487	.112
8	12.379	.135	11.605	.169	9.758	.282
12	20.527	.058	18.428	.103	17.186	.143
16	27.409	.037	23.685	.097	22.847	.118
20	32.788	.035	28.785	.092	27.579	.119

MA(1) model is a parsimonious representation of the serial dependence in both series.

How should these findings be interpreted in the framework of Section 2.1? Under the assumption that  $\rho_1 = \rho_2 = 0$ , according to model (6),  $\Delta u_t$  is generated by an MA(1) process. The sample moments (8) of the MA part of  $\Delta u_t$  are

$$(12) \quad \begin{aligned} E[w_t^2] &= \sigma_\eta^2 + 2[\alpha^2 \sigma_1^2 + 2\alpha\beta\sigma_{12} + \beta^2 \sigma_2^2] \\ E[w_t w_{t-1}] &= -[\alpha^2 \sigma_1^2 + 2\alpha\beta\sigma_{12} + \beta^2 \sigma_2^2], \end{aligned}$$

where  $w_t = \Delta u_t - \tau$ . From (12), we see that in this case  $\sigma_\eta^2 = E[w_t^2] + 2E[w_t w_{t-1}]$  is identified. Estimates of the variance and first autocovariance of  $w_t$  are

$$(13) \quad \begin{aligned} \hat{E}[\hat{w}_t^2] &= .35997 * 10^{-3} \\ \hat{E}[\hat{w}_t \hat{w}_{t-1}] &= -.04223 * 10^{-3}, \end{aligned}$$

so that

$$\hat{\sigma}_\eta^2 = .27551 * 10^{-3}.$$

From this analysis, we conclude that for the manufacturing sector in the Netherlands, TFP has been nonstationary in the seventies and eighties. Its trend is found to be stochastic. Also, one should allow for idiosyncratic effects on the two production factor labor and capital. These idiosyncratic effects appear to be negatively correlated but serially uncorrelated. Besides the first order moving average, which results from differencing TFP to render it stationary, there is not much need for autocorrelation in the technology shocks in Dutch manufacturing. This finding is at variance with the assumption made in some real business cycle models where technology shocks follow a first order autoregressive process. For instance, on detrended U.S. data, KYDLAND and PRESCOTT [1982] use a first order autoregression with  $\rho$  close to one to represent the time dependence of technology shocks. The autoregression may well be an artefact resulting from detrending using the HODRICK-PRESCOTT filter (*see* COGLEY and NASON [1992]).

## 4 Analysis of the Stationary Component of TFP

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To identify the parameter of the stationary component of TFP we use the linear recursive model of the production technology that is characterized as interrelated factor demand under uncertainty with costs of adjustment (*see* HANSEN and SARGENT, 1992). We assume that the real factor prices are set before the factor input is decided on, an assumption which has been found appropriate in previous work for data for the Netherlands (*see e.g.* PALM and PFANN [1991]).

A representative firm, produces output  $Y_t$  using as in (1) a vector of inputs  $x_t = (L_t, K_t)'$ . At time  $t$ , the production function of the firm is defined as

$$(14) \quad Y_t = (a + z_t)' x_t - \frac{x_t' A x_t}{2},$$

where  $a$  is a  $(2 \times 1)$  vector of positive constant parameters,  $z_t = (z_{1t}, z_{2t})'$ ,  $A$  is a constant symmetric, positive definite  $(2 \times 2)$  matrix.

The quadratic specification can be interpreted as the functional form of (1) or as a Taylor series approximation of the production technology (1). The advantage of the quadratic functional form is that it leads to linear decision rules. Approximations of the production function (1) by the total differential for  $\ln Y$  in (2) or by a linear quadratic specification as in (14) are widely used in empirical analyses. Although the two approximations are not formally fully consistent with each other, they allow us to investigate to what extent the two types of approximation lead to similar conclusions with respect to the dynamic properties of TFP. When the firm wants to alter the factor inputs, it faces adjustment costs which reflect the quasi-fixedness of inputs. The adjustment cost function,  $ac$ , is given by

$$(15) \quad ac_t = \Delta x_t' B \Delta x_t / 2,$$

where  $B$  is a diagonal  $(2 \times 2)$  matrix. The variable costs,  $vc$ , consist of wage and investment costs

$$(16) \quad vc_t = L_t W_t + Q_t [K_t - (1 - \delta) K_{t-1}],$$

where  $W_t$  and  $Q_t$  are the stochastic real wage costs and real price of investment goods respectively and  $\delta$  denotes the constant depreciation rate of capital.

The firm's objective is to maximize its expected real present value of profits, that is

$$(17) \quad \underset{x_t}{\text{maximize}} E \left[ \sum_{i=0}^{\infty} \varphi^i (Y_{t+i} - ac_{t+i} - vc_{t+i}) | \Omega_t \right],$$

where  $\Omega_t$  is the information set available to the firm at time  $t$ , and  $\varphi$  is a constant real discount factor. At each period  $t$ , the firm chooses contingency plans for  $x_t$  by solving the first order conditions associated with the optimal program (17) given the process for real factor prices and assuming that the processes for  $z_{it}$ ,  $i=1,2$ , are given in (3a) and (3b), but setting  $\rho_1 = \rho_2 = 0$  as suggested by the analysis of Section 3.

The empirical generating process of the real factor price  $(2 \times 1)$ -vector  $p_t = (W_t, Q_t)'$  deflated by the output price is found to be vector ARI(1,1)

$$(18) \quad (1 - ML) \Delta p_t = c^p + \varepsilon_t^p \quad \varepsilon_t^p \sim ID(0, \Sigma_p)$$

with  $c^p = (c^w, c^q)'$  being a  $(2 \times 1)$ -vector and  $M$  a  $(2 \times 2)$ -matrix of constant parameters. Given (18), the dynamic process for interrelated factor demand can be obtained by solving the first order conditions associated with (17) which yields a vector ARIMA model for  $x_t$  (see e.g. PALM and PFANN (1991) for more details).

$$(19) \quad (I - \Lambda L) \Delta x_t = \Gamma (I - M)^{-1} \Delta p_t + c^x + \nu_t^x$$

$$(20) \quad \nu_t^x = \Gamma (\iota \eta_t + \Delta \varepsilon_t),$$

where the  $(2 \times 2)$ -matrix  $\Lambda$  is the KOLLINTZAS (1985) interrelation matrix;  $\Gamma$  is a  $(2 \times 2)$ -matrix with constant parameters,  $\iota$  is the  $(2 \times 1)$  unit root vector and  $c^x$  is the  $(2 \times 1)$  intercept vector, that includes the technology drift parameter  $\tau$ . The parameters in (19) and (20) are functions of the underlying theoretical model (14)–(18)<sup>3</sup>.

More generally, the adjustment costs parameter matrix  $B$  can be assumed to be a regular  $(2 \times 2)$ -matrix, with the off-diagonal elements reflecting the trade-off of costs resulting when several inputs are altered simultaneously.

---

3. For details on the structural composition of the parameters in terms of technology parameters we refer to KODDE *et al.* (1990).

In the linear-quadratic model in closed form, however, the off-diagonal elements of the technology matrix  $A$  and the adjustment costs matrix  $B$  cannot be identified independently from each other. They appear in multiplicative form in the reduced form matrix  $\Lambda$ , that is symmetric even if  $A$  and  $B$  are not (*see* also PALM and PFANN, 1990). In a rational expectations model with a quadratic objective function, the occurrence of trade-offs in costs (the non-diagonality of  $B$ ) or in complementarity or substitutability of production factors (the non-diagonality of  $A$ ) may lead to interrelatedness in the reduced form equations of factor inputs. In the linear-quadratic framework with more than one efficiencies, interrelatedness may also result from serial cross-correlation of the efficiencies of labor and capital (the non-diagonality of  $\Sigma$ ) or from the cross elasticities of real factor costs (the non-diagonality of  $M$ ).

Substituting (18) into (19) we obtain a system of linearized decision rules being the estimable vector ARIMAX(1,1,2) process for interrelated factor demand

$$(21) \quad (1 - \Lambda L) \Delta x_t = \Gamma (I - M)^{-1} M \Delta p_{t-1} + c + \nu_t$$

$$(22) \quad \nu_t = \Gamma (\iota \eta_t + \Delta \varepsilon_t + (I - M)^{-1} \varepsilon_t^p)$$

where  $c = \Gamma ((I - M)^{-1} c^p + c^x)$ .

We assume

$$(23) \quad \eta_t \perp \varepsilon_t^p \quad \text{and} \quad \varepsilon_t \perp \varepsilon_t^p,$$

so that

$$(24) \quad E [\nu_t \nu_t'] = \sigma_\eta^2 [(\Gamma \iota) (\Gamma \iota)'] + 2\Gamma \Sigma_\varepsilon \Gamma' + (\Gamma (I - M)^{-1}) \Sigma_p (\Gamma (I - M)^{-1})'$$

and

$$(25) \quad E [\nu_t \nu_{t-1}'] = -\Gamma \Sigma_\varepsilon \Gamma'.$$

Hence  $\Sigma_\varepsilon$  can be identified from (24) if  $\Gamma$  can be consistently estimated.  $\Sigma_p$  can be identified from (24) using that  $\hat{\sigma}_\eta^2 = .27551 * 10^{-3}$  or  $\Sigma_p$  can be estimated separately from the estimation of (20).

To estimate the ARIMAX-system (20), (21), (22) and (23) we applied a 2-step residual-adjusted GLS estimation procedure which implements the Gauss-Newton algorithm and therefore yields consistent and efficient parameter estimates after one iteration provided consistent initial estimates are used (*see* e.g. PALM and ZELLNER [1980]). We used instrumental variables to obtain consistent initial estimates of the parameters of (21) and (22)<sup>4</sup>. We did not restrict the matrix  $\Lambda$  to be diagonal<sup>5</sup>. However, the matrix  $\Gamma$ , estimated from (21) turned out to be empirically diagonal. In addition to these restriction, the estimation of  $\Sigma_\varepsilon$  requires an additional assumption, implicitly induced by the overidentifying restrictions in the reduced form model (21). To compute  $\Sigma_\varepsilon$  we can use the identity that follows directly from (24) and the moving average representation of  $\nu_t = (1-\Psi L)\tilde{\varepsilon}_t$  that will be estimated instead of (22). This identity reads

$$\Gamma \Sigma_\varepsilon \Gamma' = \Psi \tilde{\Sigma}, \quad \tilde{\Sigma} = E \tilde{\varepsilon}_t \tilde{\varepsilon}_t'$$

so that

$$(26) \quad \Sigma_\varepsilon = (\Gamma)^{-1} \Psi \tilde{\Sigma} (\Gamma')^{-1}.$$

Consequently, the right hand side of (26) should be symmetric. If  $\Psi \tilde{\Sigma}$  is positive definite, then we can write  $\Psi \tilde{\Sigma} = \Phi' \Phi$  such that (26) becomes

$$\Sigma_\varepsilon = (\Phi (\Gamma')^{-1})' (\Phi (\Gamma')^{-1})$$

which is symmetric. The implicit restrictions on the elements of  $\Psi$  implied by the symmetry of  $\Sigma_\varepsilon$  have also been taken into account in the 2-step residual-adjusted GLS estimation procedure. Table 4 presents the results.

Given the estimates for the matrices  $\Gamma$ ,  $\Psi$  and  $\tilde{\Sigma}$ , we can now compute  $\Sigma_\varepsilon$  from (26). We find

$$\hat{\Sigma}_\varepsilon = 10^{-3} * \begin{bmatrix} 5.018 & 1.111 \\ 1.165 & 3.447 \end{bmatrix}.$$

The estimation of the structural parameters produced well conditioned matrix estimates for  $\Lambda$ ,  $\Gamma$  and  $\Sigma_\varepsilon$ . The determinants of  $\Lambda$  and  $\Gamma$  are positive (which is required through the underlying structural model) and  $\Sigma_\varepsilon$  is close to being symmetric. However, Hosking's multivariate portmanteau test implies that the  $(T \times 4)$  matrix of residual errors is autocorrelated. This may be solved through adding seasonal dummies or by loosening the restrictions (23).

The results we obtained for the TFP process are interesting and in line with one's intuition. The volatility of the stationary component of technology shocks  $\sigma_t^2$  is much higher than the variance of the drift component  $\mu_t, \sigma_\eta^2$ . The drift parameter plays an important role in the factor demand equations.

---

4. The list of instruments used is as follows: a constant term,  $\Delta Y_{t-2}$ ,  $LIS_{t-3}$ ,  $SIR_{t-2}$ ,  $\Delta L_{t-2}$ ,  $\Delta K_{t-2}$ ,  $\Delta W_{t-2}$ ,  $\Delta Q_{t-2}$ , where LIR and SIR are the long-term and the short-term interest rates respectively. The  $p$ -value of the test of overidentifying restrictions of the instrumental variables is .699.

5. The  $p$ -value of the WALD-statistic testing the diagonality of  $\Lambda$  yields .000.

TABLE 4

*Efficient Residual-Adjusted GLS Estimation Results of ARIMAX System.*

	Employment $\Delta L_t$	Capital $\Delta K_t$	Wage Cost $\Delta W_t$	Investment Costs $\Delta Q_t$
CONST	-.993E-2 [.000]	.659E-2 [.011]	.551E-2 [.006]	-.683E-3 [.664]
$\Lambda = \{\lambda_{ij}\}$ $i, j = 1, 2$	$\lambda_{11} = .122$ [.199]	$\lambda_{21} = .034$ [.851]		
	$\lambda_{12} = .436$ [.000]	$\lambda_{22} = .393$ [.007]		
$\Gamma = \{\gamma_{ii}\}$ $i = 1, 2$	$\gamma_{11} = .072$ [.028]	$\gamma_{22} = .079$ [.191]		
$M = \{m_{ij}\}$ $i, j = 1, 2$			$m_{11} = .109$ [.477]	$m_{21} = .157$ [.192]
			$m_{12} = .557$ [.003]	$m_{22} = .397$ [.008]
MA-coef. $\Psi = \{\psi_{ij}\}$ $i, j = 1, 2$	$\psi_{11} = .215$ [.002]	$\psi_{21} = .051$ [.000]		
	$\psi_{12} = .032$ [.000]	$\psi_{22} = .120$ [.368]		
$\Sigma = 10^{-4} * \begin{bmatrix} 1.211 & & \\ & .035 & 1.771 \end{bmatrix}$		$\Sigma_p = 10^{-3} * \begin{bmatrix} .227 & & \\ & .120 & .141 \end{bmatrix}$		
Hosking's Multivariate Portmanteau Test on Residual Autocorrelation [p-values]				
AR(5) = .175	AR(10) = .005	AR(15) = .001	AR(20) = .000	

\* p-values are given in squared brackets.

The non-stationarity of labor and capital is, just like TFP, a combination of a unit root and a trend component.

Moreover, the variance of stationary shocks in employment exceeds that of capital, which is conform the stylized fact that the production factor capital is more “fixed” (in terms of Oi [1962]) than employment.

The findings for TFP are different from those given in PALM and PFANN [1991] who estimate the set of factor demand equations (421) in levels for a shorter sample period 1971-1984 and include dummy variables for the two oil crises. They allow the productivity shocks  $s_t$  (as compared to  $z_t$  in this paper) to be generated by a first order bivariate AR process. The estimated

AR matrix is close to being symmetric with the first diagonal element being equal to .886 with  $t$ -value 1.58. This finding points at the possible presence of a unit root in the productivity shock  $s_t$ , despite the fact that when dummy variables for the oil crises were included cointegration tests for  $L_t$  and  $K_t$  did not yield much evidence in favor of a nonstationarity of the productivity shocks.

Finally the model can be used to obtain estimates of the factor efficiencies.

From (22) we derive the following expression for  $\Delta\varepsilon_t$

$$(27) \quad \Delta\varepsilon_t = \Gamma^{-1} \nu_t - \iota \eta_t - (I - M)^{-1} \varepsilon_t^p.$$

In order to compute the efficiencies for labor and capital,  $z_{it}$ ,  $i=1,2$ , we use (3) with  $\rho_i=0$ ,  $i=1,2$ , and obtain

$$(28) \quad \Delta z_t = \iota(\tau + \eta_t) + \Delta\varepsilon_t.$$

Substitution of (27) into (28) gives

$$(29) \quad \Delta z_t = \iota\tau + \Gamma^{-1} \nu_t - (I - M)^{-1} \varepsilon_t^p.$$

We can compute  $z_{1t}$  and  $z_{2t}$  from (29) recursively, using  $z_{10} = z_{20} = 1$ , using the estimate for  $\tau$  from the MA(1) process for  $\Delta A_t$  (see Table 2, row 3,  $\tau = .011278$ ), and using the estimates for  $\Gamma$  and  $M$  and the residuals  $\nu_t$  and  $\varepsilon_t^p$  from the GLS estimation of the ARIMAX system given in Table 4. Figure 3 shows  $z_{1t}$  and  $z_{2t}$ .

FIGURE 3

***Efficiencies For Labor and Capital.***

Netherlands Manufacturing 1972:1 – 1990:4

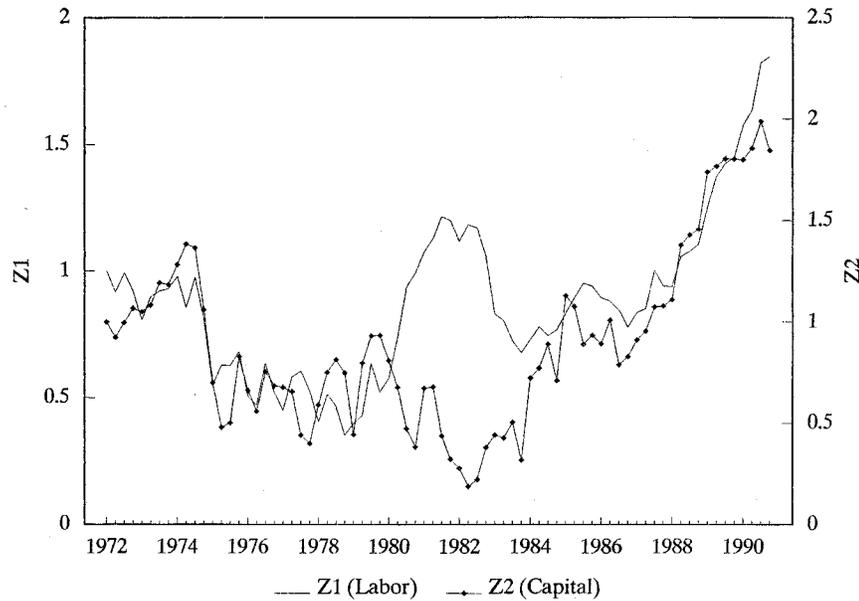
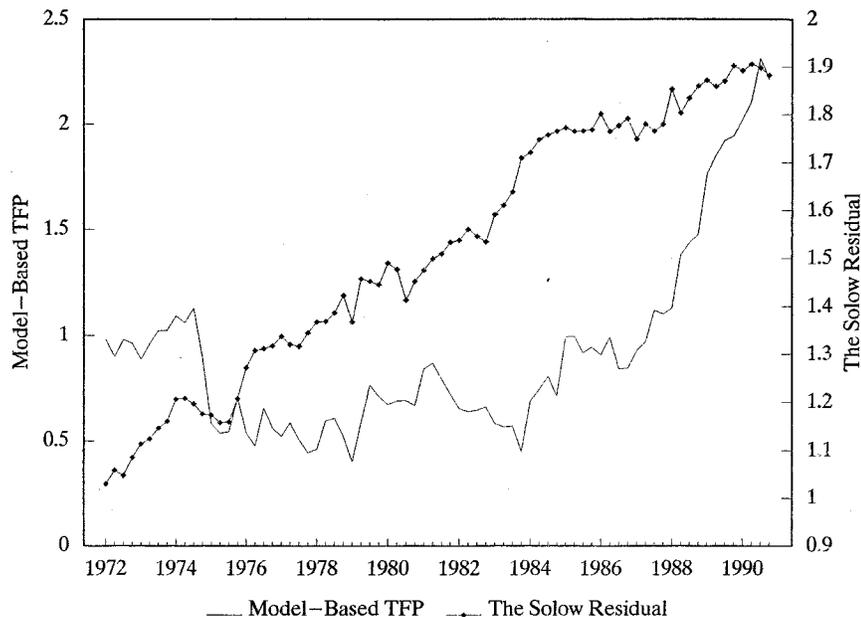


FIGURE 4

*Model Based TFP and the Solow Residual.*

Netherlands Manufacturing 1972:1 – 1990:4



The total factor productivity (model-based TFP) can then be computed from equation (14) as follows

$$(30) \quad TFP = z_{1t}L_t + z_{2t}K_t.$$

The Solow residual being recursively computed from equation (11) and the model-based TFP computed as in (30) are shown together in figure 4.

Although both series have a unit root, they are quite different. The model-based TFP is affected much stronger by the negative oil shocks of 1973 and 1979 and by the recession of the early eighties. This can be explained by the fact that the model-based TFP is directly related to real factor price shocks, whereas the Solow residual is computed on the basis of the observed labor income share alone. Negative shocks are also more persistent in TFP. This is the adjustment cost effect, that is not included in the Solow residual.

## 5 Concluding Remarks

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In this paper, we proposed a methodology to analyze the dynamic features of total factor productivity. More specifically we put forward an unobserved

components time series model (which is in fact a dynamic version of factor analysis) which nests most of the specifications used in the literature to represent the nonstationarity and serial correlation of TFP. We also showed that in some instances, the processes for the unobserved components can be identified from information on TFP only. For more complicated processes, information from the solution of the first order conditions of the intertemporal decision problem will be required in order to achieve full identification. Relying on the Euler equations only and using proxy variables for the unobserved expectational variables in these equations will generally not be sufficient to identify the processes of the components of TFP. Nevertheless, the Euler equations yield additional information about the type of nonstationarity of TFP.

In the empirical part, we illustrated the methodology by analyzing the dynamic properties of TFP for the manufacturing industry in the Netherlands, 1971-1990. To obtain an estimate of TFP, we used the method originally put forward by SOLOW [1957] which relies on the labor income share of the value of output and on the assumptions of constant returns to scale and perfect competition.

The findings of an IMA(1,1) process for the technology shocks were in line with those of several studies as far as the nonstationarity is concerned. They are also consistent with the findings for the technology shocks using the closed form solution of an intertemporal decision model. They are at variance with the assumption of a first order autoregression which underlies some of the real business cycle models.

The direct approach of analyzing TFP is simpler than studying the properties of technology shocks using the Euler conditions of the decision model. It is also quite general, in the sense that the functional form of the production function need not be completely specified. Of course, if it is known, it would be natural to use it to estimate TFP. The fact that the findings for TFP and for the system of dynamic factor demand equations are consistent with each other is an indication that the assumption of constant returns to scale when measuring TFP is probably appropriate as a first approximation. While for reason of lack of data, we had to make the assumption of constant returns to scale, one could also obtain TFP under alternative assumptions regarding returns to scale and market structure.

For instance, one could fully specify the functional form of the production function allowing for nonconstant returns to scale, estimate the parameters, possibly jointly with first order conditions for profit maximization, and generate estimates of the technology shocks.

At present, we confine ourselves to referring to NELSON [1986], HALL (1988, 1990), CABALLERO and LYONS [1990], who proposed ways of accounting for variable returns to scale and market power when estimating TFP.

We acknowledge the importance of applying the methodology we have proposed in this paper to measure TFP when returns to scale are variable. Our study, however, has made it clear that in order to do so extra identifiable sources of dynamics are required. For example, additional assumptions can be imposed on the structural model, or data on the user costs of capital (which are notoriously untrustworthy) may be used. Also, when panel data

on production are available our methodology could be extended along lines of NEUSSER [1992] to allow for spillovers from one sector to another.

Finally, we like to stress that it would be preferable to measure technology as an input instead of estimating it by computing TFP.

## APPENDIX

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Description and Sources of Quarterly Manufacturing Data in The Netherlands (SBI 2/3)

The base year of all prices and indices is 1980. All data in the model have been standardized = dividing the series by the sample mean.

$Y_t$  is a seasonally adjusted quantity index of a quarterly average of daily industrial production (National Accounts, C.B.S., The Netherlands).

$P_y$  is the producer price index of domestically sold production (SBI 2/3).

$K$  is manufacturing sector (SBI 2/3) capital stock in constant 1980 prices. Annual data provided by the Central Planning Bureau; quarterly fluctuations resemble quarterly fluctuations of manufacturing net investment in fixed assets. (Quarterly Accounts, C.B.S., The Netherlands).

$U$  is rate of capacity utilization (SBI 2/3).

$P_k$  is the producers price index of domestically placed investment goods. (Afzet Binnenland van de Industrie, SBI 2/3).

$Q$  is  $P_k/P_y$ .

$L$  is employment of 16-64 years old people working at least 20 hours per week (SBI 2/3).

$H$  is the average paid working time including overtime of all employees between 16 and 64 years old (SBI 2/3).

$Pl$  are the costs of labor in current prices per hour worked (SBI 2/3). Since the fourth quarter of 1986, this series is the quarterly updated wage cost. For the period previous to 1986.IV, this series is based on six month data on labor costs and quarterly percentage increases of wages per hour worked (SBI 2/3).

$W$  is  $Pl/P_y$ .

$LIS$  is the labor share of income (SBI 2/3) obtained from quarterly data in Algemene Industrie Statistiek en De Statistiek Werkzame Personen.

Equation (11) is computed as follows:

$$(11) \quad \frac{\Delta \hat{A}_t}{\hat{A}_t} = \frac{\Delta Y_t}{Y_t} - LIS_t \cdot \frac{\Delta(L_t * H_t)}{L_t * H_t} - (1 - LIS_t) \cdot \frac{\Delta(K_t * U_t)}{K_t * U_t},$$

FIGURE A1

***Production Volume Index.***

Netherlands Manufacturing 1971:1 – 1990:4

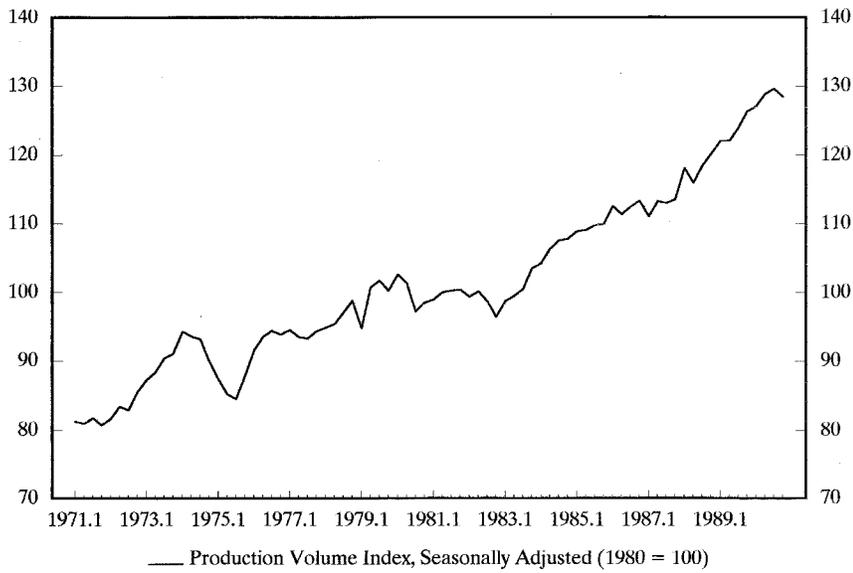


FIGURE A2

***Employment.***

Netherlands Manufacturing 1971:1 – 1990:4

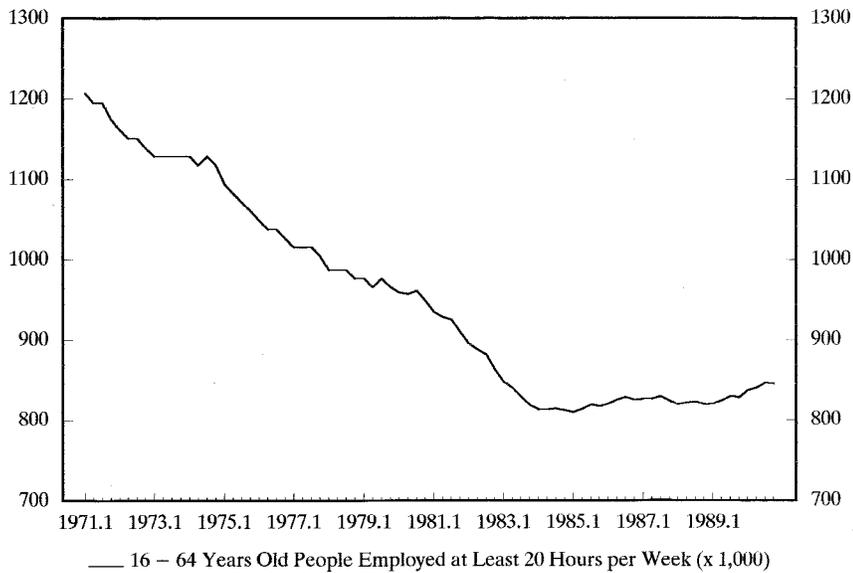


FIGURE A3

*Hourly Wage Costs.*

Netherlands Manufacturing 1971:1 – 1990:4

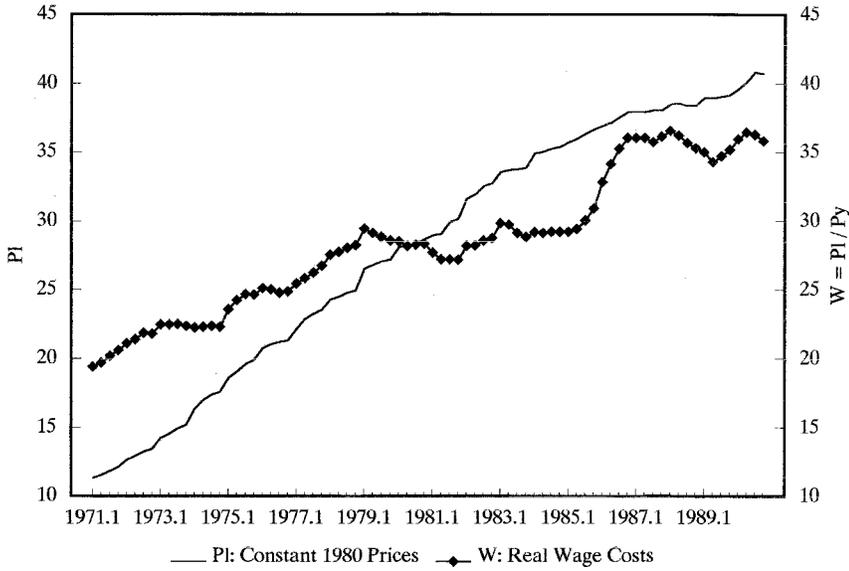


FIGURE A4

*Capital Stock.*

Netherlands Manufacturing 1971:1 – 1990:4

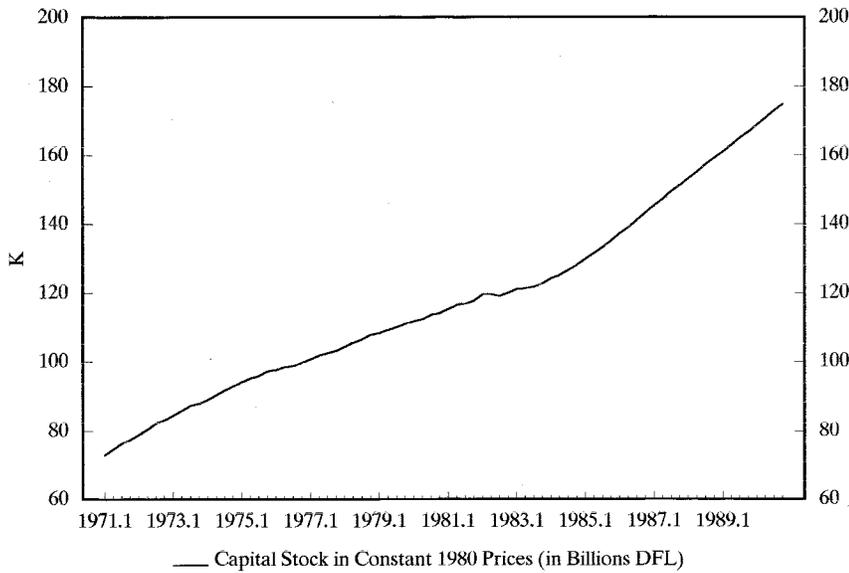


FIGURE A5

**Investment Costs.**

Netherlands Manufacturing 1971:1 – 1990:4

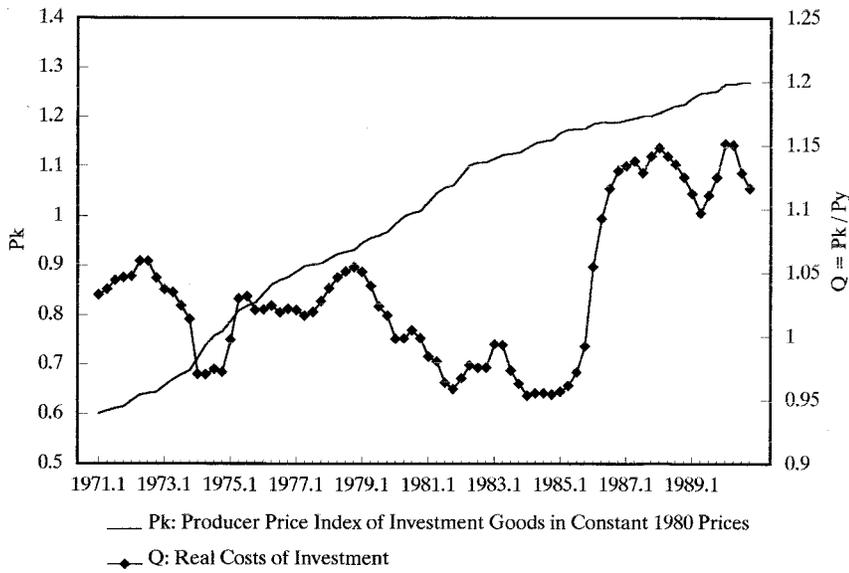
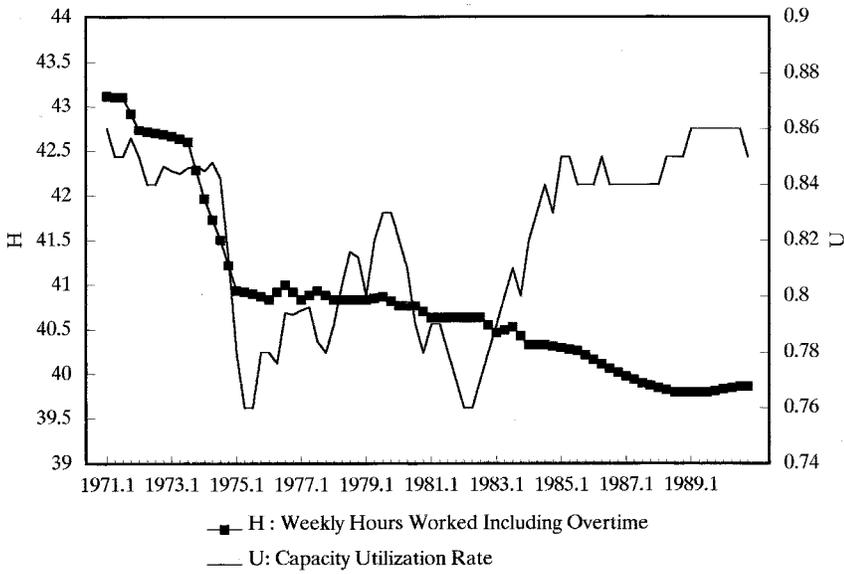


FIGURE A6

**Production Factor Utilization.**

Netherlands Manufacturing 1971:1 – 1990:4



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