APPLICATION OF COINTEGRATION ANALYSIS TO THE DEMAND FOR LABOR BY THE TURKISH PRIVATE MANUFACTURING SECTOR

A Thesis
Submitted to the Department of Economics
and the Institute of Economics and Social Sciences of
Bilkent University
In Partial Fulfillment of the Requirements
for the Degree of

MASTER OF ARTS IN ECONOMICS

by

Pelin KALE
February 1995

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I certify that I have read this thesis and in my opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Arts in Economics.

Assoc. Prof. Dr. Osman Zaim

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Assoc. Prof. Dr. Kıvılcım Metin

I certify that I have read this thesis and in my opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Arts in Economics.

Assoc. Prof. Dr. Faruk Selçuk

Approved by the Institute of Social and Economic Sciences

Director:

ABSTRACT

APPLICATION OF COINTEGRATION ANALYSIS TO THE DEMAND FOR LABOR BY THE TURKISH PRIVATE MANUFACTURING SECTOR

Pelin KALE
MA in Economics
Supervisor: Assoc. Prof. Osman Zaim
February 1995

In this study, the demand for labor by the Turkish private manufacturing sector is analyzed for three time periods; 1988 quarter 1-1993 quarter 4, 1988 quarter 1 - 1994 quarter 1, 1988 quarter 1-1994 quarter 2 to be able to capture the effects of the economic crisis of 1994 based on an approach treating employment as a function of output and real wage within an Error Correction Modeling Approach. In the search for possible long run relationships between the variables of interest, Johansen's Maximum Likelihood procedure is applied to the first difference of variables since all the data series are integrated of order 1. A unique cointegrating relationship is found for each time period. Upon testing and rejecting the exogeneity of the real wage and output series for the demand for labor, short run models are built for each period which are consistent with theory but may be subject to biases due to simultaneity between the variables of interest.

Key Words: Labor Demand, Cointegration, Error Correction Mechanisms, Turkish Private Manufacturing Sector.

ÖZET

TÜRKİYE ÖZEL İMALAT SANAYİİ SEKTÖRÜNÜN İSTİHDAM TALEBİNİN KOENTEGRASYON TEKNİĞİ KULLANILARAK ANALİZİ

Pelin KALE
Yüksek Lisans Tezi, İktisat Bölümü
Tez Danışmanı: Doç. Dr. Osman Zaim
Şubat 1995

Bu çalışmada Türkiye özel imalat sanayii sektörünün istihdam talebi, 1994 yılı ekonomik krizinin etkilerini de yakalayabilmek amacı ile, üç ayrı dönem için (1998, 1.Çeyrek - 1993, 4. Çeyrek; 1998, 1.Çeyrek - 1994, 1. Çeyrek ve 1988, 1.Çeyrek - 1994, 2. Çeyrek) reel ücret ve üretime bağlı bir fonksiyon olarak "Error Correction Modeling" (ECM) yaklaşımı ile incelenmiştir. Değişkenlerin durağanlığı birinci gecikmeleri kullamlarak fark filtresinden geçirilmeleri ile sağlanmış ve uzun dönem ikişkilerinin belirlenmesinde "Johansen's Maximum Likelihood" yöntemi kullanılmıştır. Her dönem için yalnızca bir koentegre ilişki ("Cointegrating Relationship") saptanması üzerine reel ücret ve üretim serilerinin istihdam talebi denklemi için dışsallığı ("weak exogeneity") test edilmiş ve dışsallık varsayımı reddedilmiştir. İncelenen üç dönem için de teori ile tutarlı fakat değişkenlerin eş-anlı belirlenmesinden kaynaklanan hataları da muhtemel olarak içeren, dengesizlik durumlarını yakalamak üzere uzun dönem koentegre ilişkilerden elde edilen ve literatürde "error correction mechanisms" olarak adlandırılan terimleri de kapsayan kısa dönem istihdam talep denklemleri tahmin edilmiştir.

Anahtar Kelimeler: Koentegrasyon, İstihdam Talebi, Türkiye Özel İmalat Sanayi, Hata Düzeltme Mekanizmaları.

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CHAPTER 1

INTRODUCTION

Improved understanding of influences on the demand for labor and its elasticity would contribute to many current labor market concerns such as real wage effects on both the long and the short run level of employment -which is the main focus of this study-, welfare implications, employment consequence of minimum wages and investment tax credits.

In this study, analysis of the demand for labor by the Turkish private manufacturing industry based on an approach treating employment as a function of output and real wages will be carried out within an Error Correction Modeling approach. In the search for possible long run relationships between the variables of interest, a simultaneous equation method for multivariate analysis, namely Johansen's Maximum Likelihood procedure is followed

Chapter 2 is a review of the literature on the demand for labor introducing the formal theory of labor demand for both the short and the long run with and interest in the elasticity of labor demand. Demand for labor in the long run is examined separately for the two and the multi factor cases (labor demand functions derived from technologies employing two or multi factors). Empirical work carried out on the subject considers the specification of labor demand equations and their estimation methods differentiating between homogeneous and heterogeneous labor; including both the results and problems of estimation, measurement and interpretation. Finally, application of cointegration techniques to the labor market analysis is discussed in the last section.

Chapter 3 is a preview of an important and relatively recent approach to econometric application: cointegration. Importance and usage of cointegration in econometric time series analysis, closely related literatures, and main features of the theory and practice are discussed, a stepwise analysis of the technique with explanations to useful arguments like the concept of and tests for stationarity and order of integration of time series. Two main procedures widely used for testing the existence of cointegration; namely the Engle & Granger Two Step Procedure and Johansen's Maximum Likelihood Estimator are summarised with a special emphasis on the latter which will be utilised in chapter 4 in the determination of the cointegrating relationship.

Chapter 4 is the application of cointegration analysis in a general Error Correction Modeling approach to the demand for labor by the Turkish private manufacturing sector. In this chapter, the analysis is proceeded for three time periods separately : 1988 quarter 1-1993 quarter 4, 1988 quarter 1-1994 quarter 1, 1988 quarter 1-1994 quarter 2 in order not to miss the effects of the economic crisis that became severe in 1994. Both a long run relationship between the employment of production workers, real wages and output will be searched and short run models for each period will be built.

The last chapter is devoted to conclusion. where a summary of the work performed and concluding remarks are given.

CHAPTER 2

DEMAND FOR LABOR

The first section of this chapter is a discussion of the formal theory of the demand for labor in the short run. The short run in our discussion is a period in which the only variable factor is labor; whereas the long run will a period in which all factors of production can be varied.

The second section is related to the long run demand for labor, distinguishing between the two and multi factor cases (labor demand functions derived from technologies using two or multi factors) where main focus will be on the elasticity of labor demand. Parameters of interest; the cross-price elasticity and substitution elasticities will be produced for both the two and the multi factor cases and the discussion will be preceded by differentiating between homogenous and heterogeneous labor in reviewing the related empirical work. Several methods for estimation of labor demand equations, results and problems are considered.

Finally, in the third section, applications of cointegration analysis to the labor market will be introduced.

2.1. DEMAND FOR LABOR IN THE SHORT RUN

2.1.1 Demand by the Firms:

The demand for labor in general is a derived demand from the demand for the final product for which it serves as a factor of production. The demand for labor by firms depends on some factors: technical nature of the production processes (reflected in the production function), revenue from the sales of the output and the input prices.

Let $Q_i = F(L_i, K_i)$ be the production function of firm i representing the relationship between its inputs and output
where

Q_i: Output of firm i ,
L_i: Labor input of firm i ,
K_i :Capital input of firm i .

A profit maximizing firm will set the marginal value product (price of the output multiplied by the marginal product of the factor) of each input to its marginal cost.
i.e.:

$p\partial F / \partial L_i = w$,
$p\partial F / \partial K_i = r$,   where p is the price of the output and w and r are factor prices.

The rate at which one input can be substituted for another is reflected in the slope of the isoquants, referred to as the marginal rate of technical substitution (MRTS). It shows the rate at which labor must be substituted for capital to hold the level of output constant.

$$MRTS = \frac{-dK / L}{dL / Q}$$

There is also a measure of ease with which labor can be substituted for capital which is the elasticity of substitution. It measures the relative responsiveness of the capital/labor ratio to given proportional changes in the MRTS and is given by:

$$s = \frac{d(K/L)/(K/L)}{d(MRTS)/MRTS}$$

2.1.2. Demand by the Industry and Market:

The industry labor demand curve is found by aggregating the demands of all the firms in the industry and the market demand is found by aggregating across all industries in the economy. But the shift of emphasis from the firm to the industry level or to the market has one consequence: even if the product market is purely competitive, the assumption that changes in output will have no effect on prices is no more valid. Each industry, different from the firms, faces a downward sloping demand curve. Therefore, if all firms in the industry employ more labor and increase production, it will result in a fall in product price.

2.2. DEMAND FOR LABOR IN THE LONG RUN

As the supply of labor is not perfectly elastic in the long run; the demand for labor interacts with the shape of the supply function to determine the level of wages.

The interest for the demand for labor might be due to for its own sake or for its effect on wage determination. In some cases like in unionized employment or when the supply of labor is perfectly elastic, the wage can be thought of as being unaffected by labor demand and the knowledge of wage elasticities of labor demand allows to understand the effects of exogenous changes in wage rates on the amount of labor demanded by employers. The effects of changes in the price of one type of labor on its own employment and on that of other types can be discovered by estimation of labor-demand relations alone.

Alternatively, if the employment of workers of a particular type is assumed to be fixed (completely inelastic supply of workers), the demand for labor determines the wage rate.

The study of the demand for labor also gives light to policy questions: the effects of any policy that changes factor prices will depend on the structure of the labor demand. The impact of wage subsidies, payroll tax changes, investment credits, etc. can be predicted by estimates of labor demand.
Reminding that the purpose of studying the demand for labor is to understand how exogenous changes will effect the employment and/or wage rates of workers, the main focus will be on the

relations between exogenous wage changes and the determination of employment and on only the static theory of labor demand. The dynamics of labor demand and the role of adjustment costs are ignored.

The examination of labor demand in the long run will be proceeded in two parts: the two factor case and the multi-factor case, without treating the firm and industry/market behavior separately.

2.2.1. Two Factor Case:

Many of the specific forms for the production and cost functions were initially developed for the two-factor case where the factors are labor and capital.

Let $Y = F(K, L)$ be a constant returns to scale production function with:

$F_i > 0; \quad F_{ii} < 0; \quad F_{ij} > 0.$

where K and L are homogeneous capital and labor inputs and Y is the output.

A profit maximizing firm will set the marginal value product of each factor equal to its price. Thus:

$$F_l - \lambda w = 0$$
$$F_k - \lambda r = 0$$

where w and r are exogenous prices of inputs and λ is a Lagrangean multiplier and the price of output is assumed as unity.

In the two factor linear homogeneous case, the elasticity of substitution defined previously is:

$$\sigma = \frac{d(\ln K/L)}{d\ln(w/r)} = \frac{F_l F_k}{YF_{lk}}$$

The own wage elasticity of labor demand at a constant output and constant r is:

$$\eta_{LL} = -(1-s)\sigma < 0 \text{ , (1)}$$

where

$s = \frac{wL}{Y}$ is the share of labor in total revenue.

The cross elasticity of demand (for capital services) is:

$$\eta_{LK} = (1-s)\sigma \quad (2)$$

Both (1) and (2) reflect only substitution along an isoquant (i.e. output is treated as constant). However, when the wage rate increases, the cost of producing a given output rises, and the price of the product will rise, reducing the quantity of output sold. This is the scale effect which depends on the (absolute value) of the elasticity of the product demand, η and on the share of labor in total costs. When the scale effects are added:

$$\eta'_{ll} = -(1-s)\sigma - s\,\eta \quad (1')$$

$$\eta'_{LK} = (1-s)(\sigma-\eta) \quad (2')$$

In an individual firm or particular industry which can expand or contract as the wage rate changes, scale effects on employment are relevant. For an entire economy for which the output can be considered at the level of full employment, (1') and (2') are the long run effect of changes in the wage on factor demand.

All of these measures assume that both factors are supplied inelastically to the firm and all the elasticities derived above can be achieved from the alternative approach of cost minimization. Shephard Duality Theorem states that technology may equivalently be represented by a production function or a cost function satisfying certain regularity conditions. Thus there are two ways of obtaining solutions to the derived demand functions, one method is to find a functional form of the production function and then use Lagrangean or programming techniques in order to obtain the derived demand functions. Alternatively, a functional form for the cost function can be postulated and derived demand functions can be estimated by partially differentiating the cost function with respect to input prices. The converse question of what happens to the factor prices in response to an exogenous change in factor supply can be analysed through the use of the elasticity of complementarity; defined as the percentage responsiveness of relative factor prices to a 1 percent change in factor inputs:

$$c = \frac{d\ln(w/r)}{d\ln(K/L)},$$

which is just the inverse of the definition of s.

To summarize, in the two factor case with a linearly homogeneous production technology, elasticities of substitution and complementarity can be found out from either of the production or cost functions.

Some examples of specific production and cost functions are:

<u>Cobb-Douglas Technology</u>

The production function is:

$Y = L^{\alpha}K^{1-\alpha}$

where α is a parameter and marginal products are:

$$\partial Y / \partial L = \alpha Y / L \qquad (3)$$
$$\partial Y / \partial K = (1-\alpha) Y / K \qquad (4)$$

Since the ratio of (3) to (4) is w/r under profit maximization, taking the logarithms and differentiating with respect to $\ln(w/r)$ yields $\sigma = 1$, and since σ is 1, $\eta_{ll} = -(1-\alpha)$ and $\eta_{lk} = 1-\alpha$

Constant Elasticity of Substitution (CES) Technology

The linear homogeneous production function is

$$Y = \left[\alpha L^{\rho} + (1-\alpha) K^{\rho}\right]^{1/\rho}$$

where α and ρ are parameters. The marginal products are:

$$\partial Y / \partial L = \alpha (Y / L)^{1-\rho} \qquad (5)$$
$$\partial Y / \partial K = (1-\alpha)\left(Y / K^{1-\rho}\right) \qquad (6)$$

Setting the ratio of (5) to (6) equal to w/r, taking logarithms and differentiating with respect to ln(w/r) yields:

$$\sigma = 1/(1-\rho)$$

Among the special cases of the CES function are:
(a) Cobb-Douglas function ($\rho = 0$)
(b) the linear function ($\rho = 1$)
(c) the Leontief function ($\rho = \infty$).

The CES cost function can be derived as:

$$C = Y\left[\alpha^{\rho} w^{1-\sigma} + (1-\alpha)^{\sigma} r^{1-\sigma}\right]^{1/(1-\sigma)}$$

and the demand for labor is:

$$L = \partial C / \partial w = \alpha^{\sigma} w^{-\sigma} Y$$

Two other functional forms, the generalized Leontief form of Diewert and the translog form are second order approximations to arbitrary cost or production functions. They have the advantage over CES in the two factor case that σ is not restricted to be constant but depends on the values of inputs or prices. Their cost functions are examined below.

Generalized Leontief

The cost function is:

$$C = Y\left\{a_{11}w + 2a_{12}w^{0.5}r^{0.5} + a_{22}r\right\} \qquad (7)$$

where a_{ij} are parameters.

Applying Shephard's lemma for each input, we get:

$$\frac{L}{K} = \frac{a_{11} + a_{12}(w/r)^{-1/2}}{a_{22} + a_{12}(w/r)^{1/2}}$$

In general , $\frac{-\partial(L/K)}{\partial \ln(w/r)}$ depends on all three parameters and the ratio w/r. If $a_{12} = 0$, (7) becomes a Leontief function. If $a_{11} = a_{12}$, it becomes a Cobb-Douglas type function.

Translog

The cost function is:

$$\ln C = \ln Y + a_0 + a_1 \ln w + 0.5b_1(\ln w)^2 + b_2 \ln w \ln r + 0.5b_3(\ln r)^2 + (1 - a_1)\ln r$$

Applying Shephard's lemma to each input and taking the ratios, we get

$$\frac{L}{K} = \frac{r}{w} = \frac{a_1 + b_1 \ln w + b_2 \ln r}{(1 - a_1) + b_2 \ln w + b_3 \ln r}$$

Again σ depends on all parameters and w/r. When $_{i} = 0$ for all i, the cost function reduces to a Cobb-Douglas Technology. The generalized Leontief and translog functions are useful for empirical work as they allow flexibility and contain simpler forms as special cases.

2.2.2. Several Factors

The theory of demand for several factors of production is just a generalization of the theory for the demand for two factors handled in previous parts.

Let $Y = f(X_1, X_2, \ldots, X_N)$, $f_i > 0$, $f_{ii} < 0$ be the production function of a firm (industry, market or economy). Then the associated cost function based on the demands for $X_1, X_2, \cdots, X_N$ is:

$C = g(w_1, w_2, \ldots, w_N, Y)$ where $_i$ are input prices. As in the two factor case, the profit maximization requires :

$$f_i - \lambda w_i = 0 \qquad i = 1, \ldots N \;;$$

and using the cost function,

$$X_i - \mu g_i = 0, \qquad i = 1,\dots N;$$

where

μ and λ are Lagrangean multipliers, $f_i = \frac{\partial f}{\partial X_i}$ *and* $g_i = \frac{\partial C}{\partial w_i}$.

Allen (1938) defined σ_{ij} as the partial elasticity of substitution, the percentage effect of a change in $_i / w_j$ on X_i / X_j holding output and other input prices constant as:

$$\sigma_{ij} = \frac{YF_{ij}}{X_i X_j \det(F)}$$

where

det(F) is the determinant of $\begin{bmatrix} 0 & f_1 & \cdots & f_N \\ \vdots & & f_{ij} & \\ f_N & & & f_{NN} \end{bmatrix}$, the bordered Hessian determinant of the equilibrium conditions and F_{ij} is the cofactor of f_{ij} in F. A simpler alternative definition based on the cost function is:

$$\sigma_{ij} = \frac{Cg_{ij}}{g_i g_j}$$

If the system is totally differentiated,

$$[\mathrm{F}] \cdot \begin{bmatrix} d\lambda / \lambda \\ dX_1 \\ \vdots \\ dX_N \end{bmatrix} = \begin{bmatrix} dY \\ dw_1 / \lambda \\ \vdots \\ dw_N / \lambda \end{bmatrix}$$

Holding Y and other w_k constant, $\partial X_i / \partial w_j = \frac{F_{ij}}{\lambda \det(F)}$, multiplying the numerator and denominator by $w_j X_i X_j Y$; we get:

$$\frac{\partial \ln X_i}{\partial \ln w_j} = \eta_{ij} = \frac{f_j X_j}{Y} \sigma_{ij} = s_j \sigma_{ij};$$

which is the elasticity of the demand for input i with respect to input j's price.

<u>Multi-factor Cobb-Douglas and CES Functions</u>

The N factor Cobb-Douglas cost function can be written as

$$= Y \prod_i w_i^{\alpha_i}, \qquad \sum_i \alpha_i = 1.$$

Each σ_{ij} is equal to 1 making this function quite interesting.

The N factor CES production function is:

$$Y = \left[\sum_i \beta_i X_i^\rho\right]^{1/\rho}, \qquad \sum_i \beta_i = 1.$$

As with the N factor Cobb-Douglas function, the technological parameters are $\sigma_{ij} = 1 - \rho$ for all $i \neq j$.

The Generalized Leontief

The cost function is:

$$= Y \sum_i \sum_j a_{ij} w_i^{0.5} w_j^{0.5}, \qquad a_{ij} = a_{ji} .$$

The technological parameters can be estimated from:

$$X_i = a_{ii} + \sum_j a_{ij} \left(w_j / w_i\right)^{0.5}, \qquad i = 1, \cdots N.$$

The partial elasticities of substitution are:

$$\sigma_{ij} = \frac{a_{ij}}{2\left[X_i X_j s_i s_j\right]^{0.5}},$$

and

$$\sigma_{ii} = \frac{a_{ii} - X_i}{2X_i s_i}.$$

Translog

In general, the translog cost function has the form:

$$\ln C = \ln Y + a_0 + \sum_i a_i \ln w_i + 0.5 \sum_i \sum_j b_{ij} \ln w_i \ln w_j ;$$

with

$$\sum_i a_i = 1; \qquad b_{ij} = b_{ji}; \qquad \sum_i b_{ij} = 0, \qquad \text{for all j.}$$

The first and the last equalities are a result of the assumption that C is linear homogeneous in the w_i. By Shephard's lemma,

$$\partial \ln C / \partial \ln w_i = X_i w_i / C = s_i, \qquad i = 1, \cdots, N.$$

$$s_i = a_i + \sum_{j=1}^{N} b_{ij} \ln w_j, \qquad i = 1, \cdots, N$$

The partial elasticities of substitution are:

$$\sigma_{ij} = \left(b_{ij} + s_i s_j\right) / s_i s_j, \qquad i \neq j,$$

and

$$\sigma_{ii} = \left(b_{ii} + s_i^2 - s_i\right) / s_i^2.$$

Now, the parameters of interest: the labor-demand, the cross-price and substitution elasticities have been produced for both the two and the multi factor cases. In the preceding part, the specification of the estimating equations and their estimations will be discussed in two main sections, differentiating between homogeneous and heterogeneous labor.

2.2.3. Homogenous Labor -Estimation and Empirical Issues

2.2.3.1. Estimation

Approaches to homogenous labor demand estimation can be summarised as:

Approach 1:
It relies directly on the production or the cost function. In cases of:
a) The Cobb-Douglas function; this method produces the distribution parameters.
b) CES function; its estimation is not very easy, so direct approach does not apply.
c) The generalized Leontief and Translog functions; they can be estimated directly. In the two factor case, estimation is feasible however, in the multi factor case, there is the problem of multicollinearity.

Approach 2:
It uses labor-demand conditions, either from the marginal productivity condition (derived from profit maximization), or the Shephard condition (derived from cost minimization). In cases of:

a) A CES function, this means estimating an equation like:
$\ln L = a_0 + \sigma \ln w_L + a_1 \ln Y$.
where a_i are parameters with $a_1 = 1$ if the production function is characterized by constant returns to scale.

b) A Generalized Leontief and translog functions, since the demand for labor is a nonlinear function of the factor prices, this approach is inconvenient.

In the multi-factor case, this approach involves the estimation of an equation like

$$\ln L = \sum b_i \ln w_i + a_1 \ln Y, \qquad \sum b_i = 0,$$

where constant returns to scale can be tested $(a_1 = 1)$. The multi-factor labor demand approach provides a way of testing the homogeneity of degree zero of the demand for labor for factor prices and of degree 1 in output. A similar approach can be used to examine a wage equation specified as a linear function of the logarithms of all factor quantities.

Approach 3:
It may be called the relative factor demand method. In the two factor CES case this involves the estimation of equation:

$$\sigma = 1/(1-\rho) = -\frac{\partial \ln(L/K)}{\partial \ln(w/r)}, \quad \text{(a)}$$

with $\ln(L/K)$ as a dependent variable, from which demand elasticities can be calculated. This method is invalid for the multi-factor case. as it involves the estimation of all pairs of equations like equation (a) in the CES case or in more general cases, estimation of equations like:

$$L/K = \frac{a_{11} + a_{12}(w/r)^{-1/2}}{a_{22} + a_{12}(w/r)^{1/2}}$$

$$\ln C = \ln Y + a_0 + a_1 \ln w + 0.5b_1(\ln w)^2 + b_2 \ln w \ln r + 0.5b_3(\ln r)^2 + (1-a_1)\ln r.$$

Approach 4:
It estimates the demand for labor as a part of the system of equations based on one of the approximations, like the generalized Leontief or translog forms.

The methods that have been described above are all related to estimating the constant-output labor-demand elasticity which excludes the scale effects. But, as it has been reminded before, a change in the price of labor will induce a change in output (especially if the unit of observation is a small industry). The effect of which can be measured directly or indirectly. The indirect approach takes some extraneous estimate of the demand elasticity for the product and uses $\eta'_{LL} = -(1-s)\sigma - s\eta$ to derive the labor demand elasticity including the scale effect. A direct approach estimates equations like those listed below but with output deleted.

$$\ln L = a_0 + \sigma \ln w_L + a_1 \ln Y$$

and

$$\ln L = \sum b_i \ln w_i + a_1 \ln Y, \qquad \sum b_i = 0;$$

2.2.3.2. Measurement and Interpretation

In this part, concentration is on the measurement of L and w. In the literature , alternatives of the choice of a measure of the quantity L have been total employment and total hours of work. If workers are homogeneous, working the same hours per time period, the choice is irrelevant but if they are heterogeneous along the hours worked per time period, using number of workers will lead to biases if hours per worker are correlated with factor prices or output. In studies industries, total hours is more appropriate than employment. In time series data, the choice is not much important, since there is little variation in hours per worker over time. However if dynamics of labor demand is of interest, the choice is crucial since there are significant differences in the rates at which employment and hours adjust to exogenous shocks.

The choice of a measure of the price of labor is much difficult. Most of the published data from developed countries are on average hourly earnings or average wage rates. A few countries produce data on compensation (employers' payments for fringes and wages per hour on the payroll). While most of the studies use one of the first two measures, none of them is satisfactory. The two problems faced are:

(1) Variations in the measured price of labor may be spurious results of shifts in the distribution of employment among sub aggregates with different labor costs, or of changes in the amount of hours worked at premium pay.

(2) Data on the cost of adding one worker to the payroll for one hour of actual work are not available.

The second issue is whether to treat some variables as exogenous. Ideally, the labor demand equation will be embedded in an identified model including a labor supply relation. In such a case, methods for estimating a system of equations is appropriate, both the quantity and price of labor might be treated as endogenous.

In studies based on small units, (plants, firms, small regions) supply curves to those units might be argued to be horizontal in the long run and thus wage rates might be treated as exogenous. In studies using aggregate data, this assumption has not been considered valid since Malthusion notions of labor supply were abandoned. If the supply of labor to an economy is quite inelastic even in the long run, demand parameters are best estimated using specifications that treat the quantity of labor as exogenous; production functions and variants of second -order approximations including factor quantities as regressors should be used.

In reality, it is unlikely that the labor supply is completely elastic or inelastic, so any choice than estimating production parameters within a complete system that includes supply is unsatisfactory. But since supply relations have not been estimated satisfactorily except in some sets of across-section and panel data, one has to make the appropriate choice based on the likely elasticity of supply, the availability and quality of data and about his own interest -whether factor-demand elasticities or elasticities of factor prices are under concern.

2.2.3.3. Results and Problems

2.2.3.3.1. Constant Output and Exogenous Wages .

The main parameter of interest in studying homogeneous labor is the constant-output own-price elasticity of demand. There are a number of studies that have produced estimates of this parameter. The studies can be divided into two parts: labor demand studies and production or cost function studies which use either a CES production function or a translog cost function.

Studies of the constant-output own-price elasticity of demand for homogeneous labor are:

I.Labor Demand Studies

A .Marginal productivity condition on labor (estimates of $\eta_{LL}/(1-s)$)

- Black and Kelejian (1970) , covering private nonfarm industry with quarterly data between 1948-65, with an estimate of η_{LL} =0.36
- Dhrymes (1969), using private hours and quarterly data between 1948-60, with an estimate of η_{LL} =0.75.
- Drazen et al (1984), using quarterly data of manufacturing hours of 10 OECD countries between 1961-80, with an average of country estimates of η_{LL} = = 0.21
- Hamermesh (1983), using private nonfarm, quarterly data between 1955-78, estimates η_{LL} =as 0.47.
- Liu and Hwa (1974), with private hours and monthly data between 1961-71 estimates η_{LL} = as 0.67.
- Lucas and Rapping (1970), using production hours and annual data between 1930 -65 estimates η_{LL} = as 1.09.
- Rosen and Quandt (1978), with annual private production hours data between 1930-73 estimates η_{LL} = as 0.98.

Studies listed above are based on relationships like $\ln L = a_0 + \sigma \ln w_L + a_1 \ln Y$ and since the values of s_L are unavailable for the particular samples, estimates of $\eta_{LL}/(1-s_L)$ = σ are presented. Estimates here based on a marginal productivity condition imply that the responsiveness of demand is quite consistent with constant-output demand elasticities holding other factor prices constant of between 0.2 and 0.4 (Assuming the share of labor is 2/3 and noticing that the range of most estimates is 0.67-1.09). Only Kelejian and Black and Drazen et al produce estimates that imply a constant-output demand elasticity holding other factor prices constant that is well below this range.

B. Labor demand with price of capital

- Chow and Moore (1972), with quarterly private hours data, from 1948-67 estimates the value of the sample end point η_{LL} as 0.37.
- Clark and Freeman (1980), with quarterly manufacturing data from 1950 to 76, when employment stands for labor, estimate η_{LL} as 0.33 and when hours of work stand for labor, estimate it as 0.51.
- Nadiri (1968), with quarterly manufacturing data between 1947 and 64, employment standing for labor, estimate η_{LL} as 0.15; and with hours standing for labor, estimate it as 0.19.
- Nickell (1981), using quarterly manufacturing data between 1958-74, estimate η_{LL} as 0.19.
- Tinsley (1971), using private nonfarm quarterly data between 1954-65, using employment data for labor estimates η_{LL} as 0.04 and using hours of work for labor estimate η_{LL} as 0.06.

Studies listed above in part B mostly specify the price of capital services in a labor demand equation that can be viewed as part of a complete system of demand equations. In these estimates, the own-price elasticity of labor demand is simply the coefficient of $\ln w_L$ in the equation containing $\ln L$ as the dependent variable. These estimates are substantially lower that those on part A that include only the wage rate. However the estimates in both parts are in the same narrow range.

C. Interrelated factor demand

- Coen and Hickman (1970) using annual data of private hours between 1924-40 and 1949-65 estimate η_{LL} as 0.18.
- Nadiri and Rosen (1974), using quarterly manufacturing employment between 1948-65 estimate η_{LL} for production as -0.11, and for non-production as 0.14.
- Schott (1978), using annual British industry data from 1948 to 70 estimate η_{LL} as 0.82 with employment standing for labor, and with hours standing for labor, estimate η_{LL} as 0.25.

Studies of interrelated factor demand by estimating labor and capital demand simultaneously base the labor-demand elasticities in part on the responsiveness of the demand for capital and it is likely that its price is poorly measured. These studies probably don't explain much the demand parameters of interest.

II. Production and Cost Function Studies

A. CES production function

- Brown and De Cani (1963), using annual private nonfarm hours data from 1933 to 58 estimate η_{LL} as 0.47.
- David and Van De Klundert (1965), using annual private hours data between 1899 and 1960 estimate η_{LL} as 0.32.
- Mc Kinnon (1963), with annual 2 digit SIC manufacturing data, from 1947 to 58, estimate η_{LL} as 0.29.

B. Translog cost functions

- Berndt and Khaled (1979), using annual manufacturing data from 1947 to 71, with capital, labor, energy and materials as inputs, assuming homogeneous neutral technology change, estimate η_{LL} as 0.46 and assuming nonhomothetic, non-neutral technology change, estimate it as 0.17.
- Magnus (1979), with annual enterprise sector data of Netherlands from 1950 to 76, using capital, labor , energy and materials as inputs, estimate η_{LL} as 0.3.
- Morrison and Berndt (1981) with annual manufacturing data from 1952 to 71, with capital, labor, energy and materials as inputs estimate η_{LL} as 0.35.
- Pindyck (1979), with annual data of 10 OECD countries from 1963 to 73, using capital, labor and energy as inputs estimate η_{LL} as 0.43.

Studies listed above in part II produce estimates that are roughly in agreement with those listed in parts I. A and I. B .

In fact, there is no one correct estimate of the constant-output elasticity of demand for homogeneous labor in the aggregate. The true value of the parameter changes over time as the underlying technology changes, and will differ among economies due to differences in technologies. In developed economies in the late 20th century, , the aggregate long run constant-output labor demand elasticity lies roughly in the range 0.15-0.50.

To sum up, an examination of empirical studies indicates that the labor demand elasticity can be obtained from a marginal productivity condition, from a system of factor demand equations, from a labor demand equation that includes other factor prices or from a system of equations that produces estimates of the partial elasticities of substitution among several factors of production.

2.2.3.3.2. Varying Output or Endogenous Wages

The primary focus in the long run is the constant-output labor-demand elasticity but, I would like to briefly study what happens to η' in the short run, when the output can vary. A study by Symons and Layard (1983) examined demand functions for 6 OECD countries in which only the factor prices, not the output were treated as independent variables . The estimates range from 0.4 to 2.6. These relatively large estimates suggest that there is more room for an imposed rise in real wages to reduce employment when output is let to vary.

The discussion about the homogenous labor in the aggregate, and almost all studies summarized treat factor prices including wages as exogenous. To remind, this assumption is valid only if the elasticity of labor supply is infinity which is not implied by studies on data from entire economies. The remarkable similarities of the results discussed in this section may only arise from the use of similar methods which are in fact incorrect failing to provide a proper test of the theory of labor demand.

Studies that have treated less aggregated data are listed below:

- Ashenfelter and Ehrenberg (1975), using state and local government activities of states , from 1958 to 69 estimate η_{LL} (weighted average of estimates, using employment weights) as 0.67.
- Field and Grebenstein (1980), using annual 2 digit SIC manufacturing data between 1947 and 58 estimate η_{LL} as 0.29.
- Freeman (1975)using U.S university faculty data between 1920-70 estimate η_{LL} as 0.26.
- Hopcroft and Symons (1983) using U.K road haulage data from 1953 to 80, keeping capital stock constant estimate η_{LL} as 0.49.
- Lovell (1973) with 2 digit SIC manufacturing data of 1958 estimate η_{LL} as 0.37.
- Mc Kinnon (1963)using annual 2 digit SIC manufacturing data between 1947 and 58 estimate η_{LL} as 0.29.
- Sosin and Fairchild (1984) with 770 Latin American firms between 1970-74 estimate η_{LL} as 0.2

- Waud (1968) with 2 digit quarterly SIC manufacturing data of 1954-64 estimate η_{LL} as 1.03.

The estimates of constant-output labor demand elasticities are quite similar to those summarized above . But even these units of observation are not firms or establishments upon which the theory is based. In contrast to studies of labor supply behavior based on households, there is absence of research on the empirical microeconomics of labor demand. Thus most appropriate tests of the predictions of the theory have yet to be made.

2.2.4. Heterogeneous Labor

2.2.4.1. Estimation:

If it is assumed that there are two types of labor and they are separable from nonlabor inputs, the discussion in the previous section applies. In most cases, the problem is estimating the degree of substitutability among several types of labor and other factors.

Two alternatives are possible, with the choice depending on the availability of data:

(1) A complete system of factor demand equations, a series of N equations with the L_i, $i = 1 \ldots N$ as the dependent variables and the same set of independent variables as in $\ln L = \sum b_i \ln w_i + a_1 \ln Y, \quad \sum b_i = 0$

(2) A system of equations based on one of the flexible approximations to the production or cost function (Leontief or translog forms).

Each of these approaches require data on all factor prices and quantities, while the approach using flexible forms allows the ready inference of the partial elasticities of substitution as well as the factor-demand elasticities.

As in the case of homogeneous labor, it is ideal to specify factor demands simultaneously with factor supplies. But if it is difficult to specify such a model involving homogeneous labor, it is impossible to do so for a model including several types of workers. One must be able to argue that supplies of each type of labor are either completely inelastic or completely elastic in response to exogenous changes in demand. No satisfactory choice seems to have been made in the studies that have estimated substitution among several types of labor.

2.2.4.2. Measurement and Interpretation

In empirical work estimating substitution among heterogeneous workers, separability in production of labor subaggregates from capital or other groups within the labor force is very important.

In separability of labor from capital, in many cases, there is no measure of the price or quantity of capital services. Even if such data are available, they contain large errors of measurement and it may well be argued that trying to aggregate the capital stock in an economy or even in a labor market is senseless. When substitution relations among labor subgroups in the absence of a measure of capital price or quantity are being estimated, it must be sure that labor is separable from capital. Otherwise, the estimates of labor-labor substitution will be biased.

A similar problem arises for the case of substitution among several subgroups in the labor force when it is assumed that they are separable from the rest of labor (For example, Welch and Cunningham examine substitution among three groups of young workers disaggregated by age under the assumption that the σ_{ij} of each for adult workers are identical). The estimates of the σ_{ij} between the pairs of labor subgroups being studied will generally be biased. The separability should be tested rather than imposed.

Another consideration is the choice of a disaggregation of the work force. Much of the early empirical work focused on the distinction between production and non-production workers. This was due partly to the ready availability of data and partly to the belief that such a distinction represented a comparison of skilled and unskilled labor. Recent work suggested that differences in skill between production and nonproduction workers are not so great. Most recent work has disaggregated the work force by age, race, ethnicity, sex, or a combination of these criteria.

The problem of deciding which aggregation to use and the concept of "skill" have led to the definition of some characteristics of workers. according to Welch and Rosen each worker embodies a set of characteristics, letting the data tell what the appropriate skill categories are.

2.2.4.3. Results and Problems:

A summary of the parameters of interest in the studies examining heterogeneous labor disaggregated by occupation is:

Studies of Substitution Among Production and Non Production Workers

Study	Data and Method	σbk	σwk	σbw	ηbb	ηww
	I. Capital Excluded					
A. Cost functions						
Freeman and Medoff	Manufacturing plants, 1968, 1970 and 1972, detailed industry dummy variables; CES					
	Union			0.19		
	Nonunion			0.28		

Study	Data and Method	σbk	σwk	σbw	ηbb	ηww
B. Production Functions						
Brendt and Christensen	Manufacturing, 1929-68; Translog, 1968 elasticities			4.9	-1.63	2.87
Dougherty	States, Census of Population, 1960; CES			4.1		
II.Capital Included						
A.Cost Functions						
Berndt and White	Manufacturing, 1947-71; Translog, 1971 elasticities	0.91	1.09	3.7	-1.23	0.72
Clark and Freeman	Manufacturing , 1950-76 translog, mean elasticities	2.1	-1.98	0.91	-0.58	0.22
Dennis and Smith	2-digit manufacturing 1952-73; translog, mean elasticities.	0.14	0.38	-0.05		
Denny and Fuss	Manufacturing, 1929-68; translog, 1968 elasticities	1.5	-0.91	2.06		
Freeman and Medoff	Pooled state and 2-digit manufacturing industries, 1972, translog, Union	0.94	0.53	-0.02	-0.24	0.12
	Nonunion	0.9	1.02	0.76	-0.43	0.61
Grant	SMAs, Census of Popul. 1970; translog. Professionals and managers	0.47	0.08	0.52	0.32	0.18
	Sales and clericals					
Kesselman et al.	Manufacturing, 1962-71; translog, 1971 elasticities	1.28	-0.48	0.49	-0.34	0.19
Woodbury	Manufacturing, 1929-71; translog, 1971 elasticities				-0.70	0.52
B. Production Functions						
Berndt and Christensen	Manufacturing, 1929-68; translog 1968 elasticities.	2.92	-1.94	5.51	- 2.1	2.59
Chiswick	States, Census of Population, 1910 and 1920 manufacturing;					

Study	Data and Method	σbk	σwk	σbw	ηbb	ηww
	Professionals vs others.			2.5		
Denny and Fuss	Manufacturing, 1929-68; Translog					
	1968 elasticities	2.86	-1.88	4.76		
Hansen et al.	3 and 4 digit industries, Census of Manufactures, 1967, translog;					
	highest quartile of plants			6.0	-1.3	
	lowest quartile of plants			2.0	-1.5	

The most consistent finding in the works listed above is: non production workers (presumably skilled labor) are less easily substitutable for physical capital than are production workers. The own price elasticity is lower the grater is the amount of human capital embodied in the worker.

On the issues of the ease of substitution of white for blue collar labor, and about the absolute size of the demand elasticities for each, there is little agreement among studies. However, estimated demand and substnd and substitution elasticities are higher in studies based on p functions.

Only a few studies have disaggregated labor force by educational attainment. Among them, Grant finds that the own price elasticity of demand declines the more education is embodied in the workers.

In more recent studies, a large variety of disaggregations, mostly involving age and/or race and/or sex have been used, which are listed in the table below:

Studies of Substitution among Age and Sex Groups

Category	Study	Data and Method	Types of Labor	σij	ηii
1. Substitution and Demand Elasticities					
		A.Capital Excluded			
Wages Exogenous -Cross Section	Welch and Cunningham	States, Census of Population, 1970; CES	14-15,16-17, 18-19 teenage labor	all> 0	-1.34
-Pooled Cross-section time series	Govern. of Australia	17 Australian indust. 1976-81; factor demand equations.	M < 21	all >0	-1.8
			F < 21		-4.58
			M > 21+		-0.59
			F > 21+		-2.25

Category	Study	Data and Method	Types of Labor	σij	ηii
-Time series	Johnson and Blakemore	Entire U.S economy, 1970-77; CES	average for 14 age/sex groups	1.43	
	Layard	British manufacturing, 1949-69; translog	M < 21	all > 0	-1.25
			F < 18	except	-0.31
			M 21+	F<18	-0.35
			F 18+		-1.59
		B.Capital Included			
Wages exogenous -Time series	Merrilees	Canada, Entire , economy 1957-78; factor demand equations.	Young males	mixed	0.56
			Young females		-0.44
			Adult Males		-0.07
			Adult females		-0.11
	Hamermesh	Entire economy, 1955-75; Translog, mean elasticities.	14-24	all> 0	-0.59
			25-44		-0.01
			45+		
Quantities exogenous					
-Cross Section	Grant	SMAs, Census of Population,1970; Translog.	16-24	all> 0	- 9.36
			25-44		-2.72
			45+		-2.48
-Time Series	Anderson	Manufacturing, 1947-72; Translog, 1972 elasticities.			-7.14
					-3.45
					-3.99
2. Elasticities of Complementarity and Factor Prices (Quantities exogenous)					
		A.Capital Excluded			
Cross Section	Borjas	Entire U.S economy, micro data 1975; generalized Leontief	Blacks	all > 0	-0.77
			Hispanics		-0.64
			Whites		0.001
		B.Capital Included			
Cross Section	Borjas	Census of Population, 1970; Generalized Leontief	Black males		1.02
			Females		2.9
			Hispanic Nonmigrants	all > 0 but	-2.66
			Hispanic Migrants	not females and hispan	11.98
			White nonmigr.		-0.03

Category	Study	Data and Method	Types of Labor	cij	εii
	Grant and		Youths	all>0	-0.03
	Hamermesh	SMSAs, census of	Blacks 25+	but	-0.43
		population 1970,	White M 25+	youth	-0.13
		translog.	White F 25+	vsfema.	0.19
	Grossman	SMSAs, census of	Natives	all < 0	-0.2
		population 1970;	Second generation		-0.03
		translog	Foreign born		-0.23
Time-series	Freeman	Entire US economy,	M 20-34	only	-0.38
		1950-74; translog,	M 35-64	M20-34	0.49
		mean elasticities.	F	vs F is	-0.71
				>0.	

Among above studies, the estimates of factor-demand elasticities vary greatly. However, the demand elasticity for adult men is generally lower than for other groups of workers.

As it was noted before, the elasticity of supply should guide the choice of whether to treat wages of quantities as exogenous. In the case of disaggregation by age and sex, treating quantities as exogenous and deriving elasticities of complementarity and factor price is a better choice if data on large geographical units are used. If data on a small industry or firm are used, wages should be treated as exogenous. The studies presented in part II treat quantities as exogenous and estimate these elasticities for a variety of disaggregations of the labor force and give a better indication of the substitution possibilities within the labor force disaggregated by age, race and sex than do those listed in part I.

In all the studies, the elasticities of factor prices are fairly low suggesting that the labor market can accommodate an exogenous change in relative labor supply without much change in relative wages.

Among the studies discussed in this section, only a few has tested the separability of labor from capital. Berndt and Christensen and Denny and Fuss examine this issue using the production, non-production worker disaggregation. Grant and Hamermesh disaggregate the labor force by age, race and sex. All these studies conclude that separability of labor from capital is not supported by data. They suggest that inclusion of the quantity or price of capital is necessary to derive unbiased estimates of production and cost parameters even between subgroups in the labor force. The extent of the biases induced by assuming separability has not been examined.

2.3. COINTEGRATION IN THE ANALYSIS OF THE LABOR MARKET

Existence of long run relationships consistent with theory is very important in the analysis of the labor market Brechlin (1965) and Ball & St. Cyr (1966) examining the relationship between output and employment industries and short term employment functions in British manufacturing industries consider the long run implications of their models. For UK labor markets (aggregate), Andrewes (1986) derives long run relationships and compares them across different models. Despite this interest, there has not been much work which uses cointegration analysis.

Jenkinson (1986) uses the first stage of the Engle & Granger (1987) two step procedure to determine the existence of a neoclassical long run relationship between employment, capital stock and real wages. He concludes the OLS residuals are nonstationary and rejects the existence of a cointegrating relationship. Ilmakunnas (1989) estimates an error correction mechanism for employment which has a single long run relationship (unique cointegrating vector) between employment, output and real wages for Finnish manufacturing industry.

However, these articles assume a single cointegrating vector between the variables rather than examining the existence of multiple cointegrating vectors. Alogoskaufis and Smith (1991) examine real wage equations using the Johansen procedure (1988) which allows for multiple long run relationships among wages, productivity, unemployment and hours of work and finds three cointegrating vectors.

CHAPTER 3

A PREVIEW OF COINTEGRATION

The first part of this chapter is an introduction to an important and relatively recent approach to econometric application: cointegration, while the second part covers a detailed analysis of the theory and practice of cointegration analysis.

3.1. COINTEGRATION IN ECONOMETRIC ANALYSIS

Although the non stationary nature of many economic time series has been well known for a long time: Jevons (1884) notes the need 'to avoid any variation due to the time of the year' and also to eliminate 'non periodic variations' in his study of commercial fluctuations, Hooker(1901) discusses the problems of applying the correlation theory 'where the element of time is involved' and argues for analyzing 'the deviations from the trend', the first formal study is by Yule (1926) who examined the correlation between two unrelated series such that:

(a) the series were white noise
(b) their first differences were white noise
(c) their second differences were white noise

Correlation theory worked well in case (a) with a nearly normal correlation distribution while in case (b), it resembled a semi- ellipse with excess frequency at both ends and in case (c), it was u-shaped so that the most likely correlations for the unrelated series were ± 1.

For the discrimination of spurious from real relationships, it was not until the 1960s when the methods of time series analysis began to influence econometric modeling. Though the time series techniques described by Box and Jenkins (1970) and Granger and Newbold (1977) included both multivariate and univariate techniques, the univariate methods had the most impact. Granger and Newbold (1974) noted the low values of the Durbin - Watson statistic associated with spurious regressions. Phillips (1985), with a formal analysis developed an asymptotic theory for regressions between general integrated random processes demonstrating that the distributions of the conventional statistics were not the same as those derived under stationarity. The primary problem which arises from attempting to analyse integrated series is that the usual statistical properties of first and second sample moments do not hold. Thus a different distribution theory is needed. Specifically, the regression coefficients do not converge in probability as the sample size increases: the distribution of the constant diverges and both the regression coefficient and R^2 have non-degenerate distributions. The distributions of t-tests also diverge so that there are no asymptotically correct critical values for significance tests.

A closely related literature with cointegration analysis is concerned with the debate: "time series versus econometrics" which states that by analyzing only the differences of economic time series, all information on long run relationships between the levels of economic variables is lost. Sargan(1964) had considered a class of models, later to be known as error correction mechanisms (ECM) which retained levels information in a non integrated form. Granger and

Weiss(1983) introduced the concept of cointegrated series for variables which are individually I(1) (first difference stationary) but where some linear combination of them is I(0) (level stationary) and Granger and Engle proved that cointegrated series have an ECM representation and conversely, ECMs generate cointegrated series. Later on Stock (1984) proved that if variables are cointegrated, then resulting estimates are super consistent.

Another related literature is concerned with the statistical properties and tests of time series data with unit roots (as I(1) processes must have) The mathematical-statistical literature on serial correlation includes Anderson (1942), Anderson (1948), White (1958), Fuller (1976), Dickey and Fuller (1979), Hasza and Fuller (1979), Evans and Savin (1981), (1984), Sargan and Bhargava (1983), Bhargava (1983), Phillips (1985, 86), Phillips and Durlauf (1985) and Durlauf and Phillips (1986). The main practical results are t-tests for unit roots in autoregressions based on tabulated critical values (Dickey-Fuller), tests based on the Durbin-Watson statistic (Sargan-Bhargava), and a rapidly increasing body of knowledge of the distributions of the estimators and tests when I(1) series are involved (Philips).

3.2. MAIN FEATURES OF THE THEORY AND PRACTICE OF COINTEGRATION ANALYSIS

To give an intuition about the concept of cointegration analysis, an equilibrium relationship of the form:

$Y_t = bX_t$

can be useful.

If Y_t follows an equilibrium path at each instant, then:

$Y_t - bX_t = 0$ at every t.

Out of equilibrium, we may write:

$Y_t - bX_t = \varepsilon_t$

where ε_t may be interpreted as a disequilibrium error. Engle and Granger (1987) point out that for the concept of equilibrium to have a meaning, "disequilibrium errors", ε_t should tend to fluctuate around a common mean or show systematic tendency to become smaller over. time. Equivalently, variables in equilibrium relationship should not drift too far apart and an equilibrium relationship between Y and X implies that the series are cointegrated. The reverse is also true. Furthermore, an important correspondence exists between cointegrating systems and error correction processes: the relationship between a set of cointegrating variables may be expressed by an Error Correction (EC) representation; converse of which is also true again. This result is the "Granger Representation Theorem" (Granger, 1983).

Some useful arguments in the cointegration literature and a stepwise discussion of the analysis is given below.

(1) A series Y_t is stationary if its mean, variance and autocovariances are independent of time. More formally, a stochastic process Y_t is stationary if:

(i) $E(Y_t) = \mu$ for all t.

(ii) $E\left[(Y_t - \mu)^2\right] = \gamma(0)$

(iii) $E\left[(Y_t - \mu)(Y_{t-\tau} - \mu)\right] = \gamma(\tau)$

Equations (i) and (ii) require the process to have a constant mean and variance while (iii) states that the covariance between any two values of Y from the series (i.e. autocovariances) depends only on the distance apart in time between these two values. The mean, variance, and autocovariances are independent of time.

The quantities defined by (i) to (iii) are true but unknown population measures for which from any given realization of the process, we have the sample versions defined by:

$$\hat{\mu} = \overline{Y} = T^{-1}\sum_{t=1}^{T} Y_t$$

$$\hat{\gamma}(0) = T^{-1}\sum_{t=1}^{T}(Y_t - \overline{Y})^2$$

$$\hat{\gamma}(\tau) = T^{-1}\sum_{t=\tau+1}^{T}(Y_t - \overline{Y})(Y_{t-\tau} - \overline{Y}), \quad \tau = 1,2,3,\ldots$$

If the sample autocovariances are obtained by dividing through by the sample variance we obtain the sample autocorrelations:

$$r(\tau) = \frac{\hat{\gamma}(\tau)}{\hat{\gamma}(0)}, \quad \tau = 1,2,\ldots$$

Stationarity of a series can be investigated by visual inspection of the graph of the sample autocorrelation against τ, known as the correlogram, however correlogram output is not used as a formal test of stationarity in the cointegration literature. Tests for stationarity will be explained in more detail in the following discussion.

(2) A series Y_t is integrated of order d if it becomes stationary after differencing d times. This is denoted by:

$$Y_t \sim I(d)$$

(3) The order of integration of a series may be ascertained by the application of a set of tests commonly known as tests for "unit roots".

Consider the first order autoregressive model:

$$Y_t = \beta Y_{t-1} + \varepsilon_t, \qquad t = 1,2,\ldots \qquad \text{(a)}$$

β is a real number, ε_t is a sequence of independent normal zero mean random variables with variance σ^2

The series Y_t is stationary if $\beta < 1$. If $\beta = 1$ the series is not stationary: the variance of Y_t is $t\sigma^2$,(an increasing function of time). Model above is termed a random walk with β .

In testing for unit roots, the null β equals to 1 is tested against the one-tailed alternative $\beta < 1$. If the null is true, then we have a unit root and $Y_t - Y_{t-1} = \varepsilon_t$. Furthermore the first difference of Y_t will be stationary under the null.

Model (a) with $\beta = 1$ is known as "difference stationary process". In this case, the series is said to be integrated of order 1.

By estimation of (a), the hypothesis $\beta = 1$ can be tested. However it is usual to estimate the reparametrized version:

$$Y_t - Y_{t-1} = \rho Y_{t-1} + \varepsilon_t \quad \text{and test the null } \rho = 0.$$

When we consider model (a) again, Dickey and Fuller (1979) show that, with unit roots, the least squares estimator of β is not distributed around unity, so the usual t-tests and F-test are inappropriate for testing the hypothesis. Dickey and Fuller present corrected tables for the asymptotic distributions of the t-statistic and the F-statistic which should be employed while testing the existence of unit roots.

If we want to test the stationarity or the order of integration of the series Y_t, we begin with the "Augmented Dickey-Fuller" (ADF) regression.

$$\Delta Y_t = c_1 + c_2 T + \rho Y_{t-1} + \sum_{i=1}^{m} \beta_i \Delta Y_{t-i} + \varepsilon_t$$

The t statistic on ρ is the statistic named as $\hat{\tau}$ in DF (1979). Critical values are given in Fuller (1976). As long as $\hat{\tau}$ is larger than the critical value, we cannot reject the null of a unit root. If the coefficient of time is non zero, the first difference will be time-dependent, and so the series cannot be I(1). The joint hypothesis ($\rho = 0$ and $c_2 = 0$) can be tested by means of the ϕ_3 statistic. The F-statistic computed in the usual way of imposing the restrictions in the null hypothesis on the ADF regression, should be compared with the critical values of the ϕ_3 statistic given in DF

(1981). If the value of the statistic is less than the tabulated critical value, the null cannot be rejected. Thus, the series has a unit root and is non stationary but its first difference is stationary.

(4) If two series, p_t and q_t are :

- both integrated to the same order d and
- such that a linear combination of p_t and q_t is integrated to the order b, where b < d.

then the two series are cointegrated of order d,b denoted by $\begin{bmatrix} p_t \\ q_t \end{bmatrix} \sim$ CI(d,b).

Any N dimensional vector (N>1) may be cointegrated and where N>2, cointegrating vectors need not be unique. It may also be the case that there is none and this will be so if there is no equilibrium relationship between the variables. To be more precise, if we assume that the theory suggests a relationship of the form:

$Y_t = bX_t$

For Y_t and X_t to be cointegrated it is required that:

(1) the two series should be integrated to the same order;
(2) a linear combination of the two series should exist which is integrated to an order lower than the individual series.

When both Y_t and X_t are integrated of degree 1, and $Y_t - bX_t$ is I(0), an equilibrium relationship between the two variables implies that movements in one of the two variables is matched by movements in the other; hence the difference is free of trends (neither cyclical nor seasonal) and exhibits stationarity.

In the case described above (Y_t and X_t are I(1) and $Y_t - bX_t$ is I(0)), an error correction representation such as

$$\Delta Y_t = a\Delta X_t + \lambda\left(Y - bX\right)_{t-1} + v_t$$

is a meaningful short run adjustment equation as all terms are I(0). From Stock (1984), the following results are important:

(i) With cointegrated variables, the estimates of the long run equilibrium parameters are consistent and highly efficient. They converge even more quickly in probability to the true parameter values than the least squares estimators. However these consistency results are asymptotic and in small samples, bias may be substantial.

(ii) Unlike consistency results that follow from the classical regression model, the consistency result mentioned above does not require the absence of correlation between the right hand side variable and the error term.

(iii) The short run parameter estimates are both as consistent and asymptotically efficient as those that would be obtained if the true (instead of the estimated) value of the cointegrating vector were known and used in the second stage.

(5) The cointegrating vector is the coefficient vector of a linear combination which induces cointegration. For an N dimensional vector of a time series, there may be several cointegrating vectors (maximum of N-1 possible). They can be collected into a matrix with a rank equal to the number of cointegrating vectors.

(6) If testing has established that two series are integrated of order d, the existence of cointegration between the two series can be tested for and there are two methods used widely in estimating the linear combination of variables which is integrated of order zero: the Engle and Granger Two-Step estimator and Johansen's (1988) Maximum Likelihood Estimator. The former is summarised bellow whereas the latter will be discussed separately in more detail.

The Engle and Granger two-step Procedure is performed as follows:

Stage 1: The presumed long run relationship (the cointegrating regression) $Y_t = bX_t + \varepsilon_t$ is estimated by least squares; in general including an intercept term. The fitted values from this regression are then used to test for cointegration which will be explained below. If cointegration can be accepted, $\hat{b}_{OLS}$ is a consistent estimator of b in the long run.

Stage 2: If cointegration is found, the estimated b in the first stage may be imposed upon

$$\Delta Y_t = a\Delta X_t + \lambda\left(Y - bX\right)_{t-1} + v_t$$

with the remaining parameters consistently estimated by least squares.

Testing for cointegration:

From fitting $Y_t = bX_t + \varepsilon_t$, let $\hat{\varepsilon}_t$ be the residuals. The null hypothesis $\rho = 1$ is tested in:

$\varepsilon_t = \rho\varepsilon_{t-1} + v_t$ where v_t is white noise.

If Y_t and X_t are cointegrated, this implies that ε_t is I(0). So the null being tested is that X and Y are not cointegrated. The recommended test by Engle and Granger is the augmented Dickey-Fuller (ADF) test:

$$\Delta\hat{\varepsilon}_t = -\phi\,\hat{\varepsilon}_{t-1} + \sum_{i=1}^{m}\delta_i\,\Delta\hat{\varepsilon}_{t-i}$$

In this test, the null $\rho = 1$ corresponds to $\phi = 0$. The t- statistic on ϕ is used to test the null of non-cointegration; critical values for which are given in Engle & Granger (1987).

A second test proposed by Engle and Granger in 1987 as a test that "might be used for a quick approximate result" is the cointegrating regression Durbin-Watson test (CRDWT) which is computed from the Durbin-Watson statistic from the cointegrating regression. This statistic is compared with the critical values of CRDW presented by Engle & Granger. Under the null of non- cointegration, CRDW is close to zero, the null is also rejected if the statistic exceeds the tabulated critical values.

(7) If cointegration is found in step (6), the cointegrating regression provides consistent and efficient estimates of the parameters. The short run dynamic adjustment coefficient may then be estimated by a simple and consistent procedure, as proposed by Engle & Granger.

(8) The presented analysis can be generalized to a system of equations in which a set of variables is jointly determined.

In multivariate analysis, the Engle & Granger two step procedure is performed as follows:

First of all X_t should be pretested to ensure that each component is integrated to the same order. Suppose that each is $I(1)$. Then a cointegrating regression is run. We get:

- A set of residuals on which tests for cointegration will be carried out.
- When cointegration is accepted, consistent estimates of the equilibrium equation parameters.

For each possible choice of normalization (a variable is normalized if its coefficient is set to 1 in the cointegrating regression), procedure described above is repeated. In the second stage, an error correction dynamic equation for each equation is specified. When $r > 1$, the Engle & Granger estimator is less satisfactory.

In the regression:

$Y_t = dX_t + \varepsilon_t$,

d will not be equal to $1/b$ in the regression $X_t = bY_t + v_t$. Different estimates from a set of Engle and Granger cointegrating regressions can be interpreted as differences due to sampling variance or might be reflections of distinct equilibrium vectors. It has been suggested (Hall & Henry, 1988) that OLS will detect only the minimum variance vector, so that the former interpretation is correct but this result has not been established yet.

In the two step estimation procedure, the restriction deriving from the long run solution (estimated in the first stage) needs to be imposed on each equation in the system in the second stage error- correction representations. These equations can be estimated singly; the cointegrating vector placed in each equation imposes the cross equation restrictions implied by cointegration and are required for efficient estimation. The cross-equation restrictions reflect the long run relationships between the levels of the variables in the system.

(9) In more than two variables case, Engle & Granger two step procedure has some limitations mostly due to the possible existence of multiple cointegrating vectors. An important area of recent research is concerned with deriving maximum likelihood tests for the presence of more than one cointegrating vector. Such an approach is presented by Johansen and Juselius which is commonly referred to as the "Johansen's Maximum Likelihood Estimator" and will be discussed in more detail.

Johansen's Maximum-likelihood Estimator:

The maximum-likelihood approach of Johansen & Juselius (1990) gives both consistent ML estimates of the whole cointegrating matrix, producing a likelihood ratio statistic for the maximum number of distinct equilibrium vectors and that the LR statistic has an exact known distribution which is a function of just one parameter. Test statistics in Engle & Granger approach have a distribution which is a function of the whole data-generation process that is unknown. Given the distributional properties of the ML estimator, specification tests can be carried out on the cointegrating vectors.

Derivation and applications of Johansen maximum-likelihood estimator are found in Johansen(1988), Johansen & Juselius (1990), Hall (1989), Muscatelli (1990), and Hall and Henry (1988).

Johansen's estimation method uses the error correction representation of the VAR(p) model with Gaussian errors:

$$\Delta X_t = \mu + \Gamma_1 \Delta X_{t-1} + \ldots + \Gamma_{p-1} \Delta X_{t-p+1} + \Pi X_{t-p} + \Phi D_t + \varepsilon_t \qquad (1)$$

where

X_t is mX1 vector of I(1) variables;

D_t is sX1 vector of I(0) variables;

$\Gamma_1, \Gamma_2, \ldots, \Gamma_{p-1}, \Pi$ are mXm matrices of unknown parameters;

Φ is a mXs matrix;

$\varepsilon_t \approx N(0, \Lambda)$.

Attention is on the long run parameter vector Π. With r cointegrating vectors $(1 \le r < p)$ Π has a rank of r and can be decomposed as $\Pi = \alpha\beta'$ with α and β both $m \times r$ matrices. where β is the vector of parameters on the variables in the cointegrating relationships and α measures the strength of the cointegrating vectors.

Johansen's procedure is interpreted based on the premise that variables are integrated of order 1, I(1). If some or all of the series are integrated of a higher order than 1 then a more complicated procedure is required. The first step in Johansen's procedure is thus to test the order of integration of the variables which can be performed through the ADF tests for unit roots.

Johansen's maximum likelihood procedure estimates (1) subject to the hypothesis that Π has a reduced rank; r < m.

$$H(r) = \Pi = \alpha\beta' \text{ where } \alpha \text{ and } \beta \text{ are mXr matrices.}$$

The trace and maximum eigenvalue test statistics proposed by Johansen are computed for the testing of the above hypothesis.

The number of cointegrating vectors is determined sequentially starting with $r = 0$ (no cointegrating relation) and if it is rejected, the hypothesis that there are at most 1 ($r \leq 1$) cointegrating vector is tested and the procedure follows to $r \leq 2$ upon the rejection of $r \leq 1$ and so on until failure to reject a value of r. Finally,

(1) If $r = 0$ cannot be rejected then there are no cointegrating relationships among X_t.
(2) If $r = m$ cannot be rejected, then X_t has a stationary process.
(3) The results provide evidence in favor of cointegration only when 0<r<m.

Derivation of the maximum likelihood estimator and the related tests:

In estimating the parameters of model (1), Johansen defines:

$$Z_{0t} = \Delta X_t$$

$$Z_{1t} = \Delta X_{t-1}, \ldots, \Delta X_{t-p+1}, D_t \quad and \quad 1$$

$$Z_{pt} = X_{t-p}$$

Γ is a matrix of $\Gamma_1, \Gamma_2, \ldots, \Gamma_{p-1}, \Phi, \mu$.

Now, the model becomes:

$$Z_{0t} = \Gamma Z_{1t} + \Pi Z_{pt} + \varepsilon_t, \qquad t = 1, \ldots T$$

For fixed Π, ML estimates consists of a regression of $Z_{0t} - \Pi Z_{pt}$ *on* Z_{1t} giving :

$$\sum_{t=1}^{T} Z_{0t} Z'_{1t} = \Gamma \sum_{t=1}^{T} Z_{1t} Z'_{1t} + \Pi \sum_{t=1}^{T} Z_{pt} Z'_{1t} \quad (2)$$

The product moment matrices are:

$$M_{ij} = T^{-1} \sum_{t=1}^{T} Z_{it} Z'_{jt}, \qquad i, j = 0, 1, p.$$

then (2) is:

$$M_{01} = \Gamma M_{11} + \Pi M_{p1}$$

or

$$\Gamma = M_{01} M_{11}^{-1} - \Pi M_{p1} M_{11}^{-1}.$$

This leads to the definition of residuals:

$$R_{0t} = Z_{0t} - M_{01}M_{11}^{-1}Z_{1t},$$
$$R_{pt} = Z_{pt} - M_{pt}M_{11}^{-1}Z_{1t}.$$

i.e. residuals we would obtain by regressing ΔX_t and X_{t-p} on $\Delta X_{t-1},\ldots,\Delta X_{t-p+1}, D_t$ *and* . The concentrated likelihood function is:

$$|\Lambda|^{-T/2}\exp\left\{-\sum_{t=1}^{T}\left(R_{0t}-\Pi R_{pt}\right)'\Lambda^{-1}\left(R_{0t}-\Pi R_{pt}\right)/2\right\}$$

The residual product moment matrices are defined as:

$$S_{ij} = T^{-1}\sum_{t=1}^{T} R_{it}R'_{jt} = M_{ij} - M_{i1}M_{11}^{-1}M_{1j};\quad (i,j=0,p)$$

are computed and a solution to the eigenvalue problem:

$$\left|\lambda S_{pp} - S_{p0}S_{00}^{-1}S_{0p}\right| = 0$$

is obtained.

Let $\hat{\lambda}_1 > \hat{\lambda}_2 > \ldots > \hat{\lambda}_m$ be the solution of the above problem and $\hat{\ } = (\hat{v}_1, \hat{v}_2, \ldots, \hat{v}_m)$ be the corresponding eigenvectors normalised by $\hat{\ }' S_{pp}\hat{V} = I_m$. Then the ML estimators of β and α are given by:

$$\hat{\beta} = (\hat{v}_1, \hat{v}_2, \ldots, \hat{v}_r),$$
$$\hat{\alpha} = S_{0p}\hat{\beta}$$

The maximised log-likelihood function of the VAR(p) model under the cointegration hypothesis

$$H(r):\ \Pi = \alpha\beta', \quad \textit{equivalent to} \quad Rank(\Pi) = r$$

is given by:

$$L_R(\tilde{\theta}) = \frac{-n}{2}\log|S_{00}| - \frac{n}{2}\sum_{i=1}^{r}\log(1-\hat{\lambda}_i).$$

and the unrestricted log-likelihood function, which is equivalent to testing r = m is given by:

$$H(m):\ L_u(\hat{\theta}) = \frac{-n}{2}\log|S_{00}| - \frac{n}{2}\sum_{i=1}^{m}\log(1-\hat{\lambda}_i),$$

Above, T is the number of observations and $\tilde{\theta}$ *and* $\hat{\theta}$ are the restricted and unrestricted estimators of the parameters of the VAR(p) model. The trace statistic proposed by Johansen for testing H(r) against H(m) is given by:

$$J_T = 2\left[L_u\left(\tilde{\theta}\right) - L_R\left(\hat{\theta}\right)\right],$$
$$= -n\sum_{i=r+1}^{m}\log\left(1-\hat{\lambda}_i\right)$$

and the maximal eigenvalue statistic for testing H(r-1) against H(r) is given by:

$$\lambda_{\max} = -n\log\left(1-\hat{\lambda}_r\right)$$

The critical values for the trace and maximal eigenvalue statistics are given in Osterwald-Lenum (1990).

Testing for Weak Exogeneity (Restrictions on α Matrix):

If for some i, α_i = 0 then ΔX_{it} is weakly exogenous for α and β in the sense that the conditional distribution of ΔX_tgiven ΔX_{it} as well as the lagged values of X_t contains the parameters α and β whereas the distribution of ΔX_{it} given the lagged X_t does not contain the parameters α and β. The condition of weak exogeneity holds only for the case when the parameters of interest are the long run parameters α and β. Johansen and Juselius (1990) give a discussion of this topic.

According to a theorem by Johansen & Juselius, (Johansen & Juselius (1990)): Under the hypothesis $\alpha = A\Psi$ where A is a $m \times q$ matrix, the maximum likelihood estimator of β is found as follows:

First of all, it is convenient to introduce $B \quad (m \times (m-q)) = A\perp$ such that $B'A = 0$. Then the hypothesis can be expressed as $B'\alpha = 0$ and the concentrated likelihood function as:

$$(i) \;\; A'(R_{0t} - \alpha\beta' R_{pt}) = A'R_{0t} - A'A\Psi\beta' R_{pt}$$
$$(ii) \;\; B'(R_{0t} - \alpha\beta' R_{pt}) = B'R_{0t}$$

Since (ii) does not contain the parameters $\Psi$and β, it is factored out and the following are defined:

$$\Lambda_{aa} = A'\Lambda A,$$
$$\Lambda_{ab} = A'\Lambda B$$
$$S_{ap.b} = S_{ap} - S_{ab}S_{bb}^{-1}S_{bp}$$

where

$$S_{ap} = A' S_{0p}$$
$$S_{ab} = A' S_{00} B$$
$$S_{bb} = B' S_{00} B$$
$$S_{bp} = B' S_{0p}$$

The factor corresponding to the marginal distribution of $B'R_{0t}$ is given by:

and gives the estimate

$$\hat{\Lambda}_{bb} = S_{bb} = B' S_{00} B$$

and the maximised likelihood function from the marginal distribution

$$L_{\max}^{-2/T} = |S_{bb}| / |B'B|$$

The other factor corresponds to the conditional distribution of $A'R_{0t}$ and R_{pt} conditional on $B'R_{0t}$ and is given by:

$$-\sum_{t=1}^{T} (A' R_{0t} - A' A \Psi B' R_{pt} - \Lambda_{ab} \Lambda_{bb}^{-1} B' R_{0t})' \times \Lambda_{aa.b}^{-1} (A' R_{0t} - A' A \Psi \beta' R_{kt} - \Lambda_{ab} \Lambda_{bb}^{-1} B' R_{0t}) / 2$$

From the theory of the multivariate normal distribution, the parameters $\Lambda_{bb}, \Lambda_{ab}\Lambda_{bb}^{-1}$, and $\Lambda_{aa.b}$ are variation independent and hence the estimate of $\Lambda_{ab}\Lambda_{bb}^{-1}$ is found by regression for fixed Ψ and β giving:

$$\hat{\Lambda}_{ab} \Lambda_{bb}^{-1} (\Psi, \beta) = (S_{ab} - A' A \Psi \beta' S_{pb}) S_{bb}^{-1}$$

and new residuals defined by:

$$\tilde{R}_{at} = A' R_{0t} - S_{ab} S_{bb}^{-1} B' R_{0t}$$
$$\tilde{R}_{pt} = R_{pt} - S_{pb} S_{bb}^{-1} B' R_{0t}$$

The maximum likelihood estimator of β is found by solving:

$$\left| \lambda S_{pp.b} - S_{pa.b} S_{aa.b}^{-1} S_{ap.b} \right| = 0$$

giving $\hat{\lambda}_1 > \ldots > \hat{\lambda}_{q+1} = \ldots = \hat{\lambda}_m = 0$ and $\hat{\ } = (\hat{v}_1, \ldots \hat{v}_m)$ normalised such that

$$\hat{\ }' S_{pp.b} \hat{V} = I$$

Taking $\hat{\beta} = (\hat{v}_1, \ldots \hat{v}_r)$ which gives estimates:

$$\hat{\Psi} = (A'A)^{-1} S_{ap.b} \hat{\beta}$$

and

$$\hat{\alpha} = A\hat{\Psi} = A(A'A)^{-1}A'(S_{0p} - S_{00}B(B'S_{00}B)^{-1}B'S_{0p})\hat{\beta},$$
$$\hat{\Lambda}_{aa.b} = S_{aa.b} - A'A\hat{\Psi}\hat{\Psi}'A'A = S_{aa.b} - A'\,\hat{\alpha}\hat{\alpha}'A$$

and maximised likelihood function

$$L_{\max}^{-2/T} = |B'B|^{-1}|A'A|^{-1}|S_{bb}||S_{aa.b}|\prod_{i=1}^{r}(1-\hat{\lambda}_i) = |S_{00}|\prod_{i=1}^{r}(1-\hat{\lambda}_i)$$

The likelihood ratio test statistic of restrictions on α in the restricted model where the rank of β is restricted to r is given by:

$$-2\ln(Q, H'/H) = T\sum_{i=1}^{r}\ln\left\{\frac{1-\hat{\lambda}_i'}{1-\hat{\lambda}_i}\right\}$$

where

H':hypothesis restricting α,
H: hypothesis that there are r cointegrating vectors,
$\hat{\lambda}_i'$: eigenvalues obtained from restricted α,
$\hat{\lambda}_i$: eigenvalues obtained from unrestricted α.

The asymptotic distribution of the test statistic is given by a χ^2 distribution with $r\times(p-m)$ degrees of freedom.

CHAPTER 4

APPLICATION OF COINTEGRATION ANALYSIS TO THE DEMAND FOR LABOR BY THE TURKISH MANUFACTURING SECTOR

The first section of this chapter is a detailed description of the data used, its sources and related problems

In the second section, the existence of long run relationships among employment, real wage and output series for the Turkish private manufacturing sector is tested using an error correction model (ECM) approach and applying Johansen's Maximum Likelihood procedure. The analysis will be carried out for the three time periods: 1988 quarter 1 (88Q1)-1993 quarter 4 (93Q4), 1988 quarter 1 (88Q1)-1994 quarter 1 (94Q1) and 1988 quarter 1 (88Q1)-1994 quarter 2 (94Q2). The need for this distinction rose due to the economic crisis that could be felt by the first quarter of 1994 and became severe in the second quarter with adverse effects on the manufacturing sector.

4.1. DATA

Data series used in this study are:

Employment series is taken from the quarterly publication of State Institute of Statistics `Indexes of Industrial Production, Production Workers and Production Hours in the Manufacturing Sector`; gathered from the quarterly manufacturing surveys of State Institute of Statistics of Turkey.

The nominal wage series is gathered from the quarterly manufacturing surveys of State Institute of Statistics of Turkey and real wage series is obtained by deflating it by the quarterly whole sale price indices (TEFE) for the private manufacturing sector which are averages of three monthly values for each quarter. The obtained real wage series is then indexed such that 88Q1 = 1.

The output series are directly taken from the State Institute of Statistics' quarterly publication "Indexes of Industrial Production, production Workers, and Production Hours Worked in the Manufacturing Sector" which is calculated based on value added quantities rather than gross output and reindexed such that 88Q1 = 1.

The main data bottleneck faced in this study stemmed from the wage data since quarterly data on wages for the manufacturing industry with a distinction between the private and public sectors was available starting by the first quarter of 1988 and did not date back any further. Thus the period of study could not be extended backwards.

The real wage, employment and output data are not adjusted seasonally so seasonal dummies are used in the analysis. Throughout the analysis, all variables are expressed in logarithms and % changes are approximated by first differences in logarithms.

The data series are given in Table 19, appendix D and the plots of the levels and percentage changes are given in the graphs. Graphics 1, 2 and 3 are separate plots of the levels of employment, real wages and output. Graphic 4 is the plot of employment and output series, Graphic 5 is the plot of real wage and employment series and Graphic 6 shows all the three series' plots. Graphics 7, 8 and 9 are plots of first differences.

With a closer look at the data, within the period of interest, the number of production workers has been decreasing. Employment of production workers by the private manufacturing sector declined by 21% by the fourth quarter of 1993 compared to quarter 1 of 1988. And by 4.72 % from 1988 Q1 to 1994Q1 and by 4.60.% from 1994Q1 to 1994Q2.

While employment exhibits a decreasing pattern, i
t is observed that levels of production has been increasing during 1988-1993. In the private sector, production index increased up to 151 in the fourth quarter of 1993 from 100 in the first quarter of the base year 1988 but it was 84.7 in the first quarter of 1994 and 80.8 in the second quarter of 1994.

When the pattern of real wages is examined, it is observed that private manufacturing sector real wages increased by 168 % from 1988.Q1 to 1993.Q4 and during 93Q4 and 94Q1 and 94Q1 and 94Q2, it declined by 5.12% and 30.75% respectively.

It is quite reasonable to suggest that the fall in the level of production workers while output is expanding might be due to the choice of capital intensive technologies which stems from the sharp increase in real wages resulting in labor's becoming a relatively expensive input. The increase in the real wage rates force firms towards automation and reduced employment to cut down costs.

The underlying relationship between the level of employment, output and real wages will be explored and discussed in the next section both for the short run and long run dynamics of the Turkish private manufacturing industry.

4.2. ANALYSIS OF THE SHORT AND THE LONG RUN BEHAVIOR OF THE DEMAND FOR LABOR BY THE TURKISH PRIVATE MANUFACTURING INDUSTRY

Literature on estimating labor demand functions had been discussed in chapter 2, and as it was stated, specification of labor demand functions can be performed in two ways:

1) treating employment as a function of output with a possible role for real wages which assumes that demand constraints are binding in the labor market. This specification have been used by Brechling (1965), Nickell (1984), Wren-Lewis (1986), Ilmakunnas (1989).

2) assuming market clearing as presented by Symons (1981), including capital stock, real wages and the real prices of raw materials. This relationship is used by Nickell (1984), Symons & Layard (1984), Newell & Symons (1985), Jenkinson (1986).

In this study, focus will be on the first specification with the labor market constrained by demand which is quite a reasonable assumption for the Turkish labor market due to the existence and persistence of excess supply of labor and a relationship of the form

$$\beta_0(L)L_t = \delta_0 + \beta_1(L)Y_t + \beta_2(L)W_t + u_t$$

where

L_t :log of employment

Y_t :log of output

W_t :log of real wage and

$\beta_i(L)$, $i = 0,1,2.$: lag operators

u_t :error term

The existence of long run relationships consistent with theory will be analysed by cointegration techniques. In the works of Jenkinson (1986) using the first stage of Engle & Granger two step procedure to determine the existence of a single neoclassical long run relationship between employment, capital stock, real wages and real input prices; Ilmakunnas estimating an ECM for employment which has a long run relationship between employment, output and real wages; Burgess searching for a long run employment-capital relationship; it is assumed that there exists a single cointegrating relationship between the variables rather than testing it. In this study, using Johansen's procedure, possibility of more than one long run relationship among real wages, output and employment is allowed and tested.

Johansen 's approach which was examined in detail in chapter 3, shortly considers the general ECM which is a VAR model as:

$$\Delta x_t = \Gamma_1 \Delta x_{t-1} + \ldots + \Gamma_{k-1}\Delta x_{t-k+1} + \Pi x_{t-k} + Bz_t + v_t \quad (1)$$
$$v_t \approx D(0,\Omega)$$

where Δ is the first difference operator, x_t is an mx1 vector, z_t. is an sx1 vector of I(0) variables, $\Gamma_1 \ldots \Gamma_{k-1}, \Pi$ are parameters,. Ω is the disturbance covariance matrix.

The first step in the Johansen procedure is to test the order of integration of the variables in the system. Tables A1, A2, A3, B1, B2, B3 and C1, C2, C3 in appendices A, B and C report the Augmented Dickey Fuller and Dickey Fuller test statistics for the three periods of study testing the nonstationarity hypothesis of employment, real wage and output series (L, W and Y) over the period of study. As a reminder, ADF test of unit roots is based on the following regression.:

$$\Delta x_t = \alpha_0 + \delta x_{t-1} + \sum_{i=1}^{n} \Phi_i \Delta x_i + e_t$$

where Δ is the first difference operator and e_t is a stationary random error. The Dickey-Fuller (DF) test is based on the above regression when $\sum_{i=1}^{n} \Phi_i \Delta x_{t-i}$ is deleted from the right hand side. The null hypothesis is that x_t is a nonstationary series and is rejected when δ is significantly negative (if the actual test statistic is less than the critical value).

For the period 88Q1-93Q4when tables A1, A2, A3, are examined, it is concluded that the ADF and DF tests fail to reject the null hypothesis of stationarity for all the series (the real wage, output and employment series) and thus none of the series is level stationary; so to test for integration of order 1, the first differences of each series is computed as:

$$DL = L_t - L_{t-1}$$
$$DW = W_t - W_{t-1}$$
$$DY = Y_t - Y_{t-1}$$

and tested for stationarity. The results are given in Tables A4, A5 and A6. It is observed that the tests reject the null of nonstationarity and thus it is concluded that employment, real wage and output series are integrated of order 1.

For the period 88Q1-94Q1, it can also be concluded that the tests fail to reject nonstationarity of levels (as reported in tables B1, B2, B3) but reject the nonstationarity of first differences (as reported in tables B4, B5, B6); thus during this period, the series are all I(1).

However, for the period 88Q1-94Q2, though the tests again fail to reject the nonstationarity of levels and fail to reject that of the first differences, it is observed that the crisis had the most effect in this period and mostly on the stationarity of the real wage series which can be attributed to both its effects on the nominal wage rates and on the wholesale price indices.

Since all the series are I(1), Johansen's Maximum Likelihood procedure can be applied to find out the cointegrating relations. From the estimation of the dynamic system given by (1) where X_t is the vector of employment, real wage and output, the parameter matrix which will be of concern is Π that can be decomposed in an α and β matrix:

$$\Pi = \alpha\beta'$$

where α and β are mxr matrices with m being the number of equations (a total 3 equations; one equation for each of the real wage, output and employment series in this study) and r is both the rank of Π and the number of cointegrating vectors.

Notice that if Π is of full rank; i.e. r = m = 3, then the long run solution for x_t defined in (1) is unique and equal to a vector of constants. However since X is I(1), this is false and Π cannot be of full rank . As explained by Johansen while the rank of Π determines the number of cointegrating relations, α matrix in the decomposition of Π measures the average speed of adjustment towards the long run equilibrium.

To determine the number of cointegrating vectors, Johansen's procedure is carried out for model (1) separately for the three time periods under two different assumptions. The first case will test the number of cointegrating vectors based on both the maximal eigenvalue and the trace test statistics assuming that there is no constant term in the model; whereas in the second case, trend in both the model and the data generating process is allowed.

A. TESTING FOR COINTEGRATION UNDER THE ASSUMPTION OF NO DETERMINISTIC TRENDS IN THE VARIABLES

It is assumed that μ in model (1) is equal to 0; i.e. there are no deterministic trends in the variables and the data generation process (DGP) does not contain a trend term either. For this case, actual and critical values of the tests for the rank of Π obtained from the likelihood ratio tests, derivations of which were given in Chapter 3, namely the trace and maximal eigenvalue tests are given in tables A7 and A8 for 88Q1-93Q4, tables B7 and B8 for 88Q1-94Q1 and tables C7 and C8 for 88Q1-94Q2.

i)Testing Through the Maximal Eigenvalue Test statistic:

Tests based on the maximal eigenvalue of the stochastic matrix test $H(r-1)$ against $H(r)$ in other words Π has rank $r-1$ against it has rank r.

For the period 88Q1-93Q4, starting with the hypothesis $r=0$ against $r=1$, examining table A7 gives an actual value of the statistic is 38.9124 which is larger than both the 95% and 90% critical values, 22.0020 and 19.7660 respectively. So, the hypothesis $r=0$ is rejected and the hypothesis that there is at most one cointegrating vector $(r \leq 1)$ is tested against $r=2$. Actual value of the test statistic (9.6377) is less than the 95 % and 90 % critical values; 15.6720 and 13.7520. Thus $r \leq 1$ cannot be rejected, and it is concluded that there is a unique cointegrating relationship.

For the period 88Q1-94Q1, table B7 reports the results. $r=0$ against $r=1$ is rejected with an actual value of the test statistic 25.8464 and 95 % and 90 % critical values of 22.0020 and 19.7660. Proceeding to testing $(r \leq 1)$ against $r=2$, $(r \leq 1)$ cannot be rejected with an actual test statistic of 8.9288 and 95 % and 90 % critical values of 15.6720 and 13.7520. The number of cointegrating vectors is then 1

For the period 88Q1-94Q2, table C7 reports the results and it is observed that $r=0$ against $r=1$ is rejected with an actual value of the test statistic 23.9439 and 95 % and 90 % critical values of 22.0020 and 19.7660. Thus there is a unique cointegrating vector.

ii) Testing Through the Trace Test Statistic

If Johansen's trace test, results of which are given in tables A8, B8 and C8, testing $H(r)$ against $H(m=3)$ is used:

For the period 88Q1-93Q4, as given in Table A8; $r=0$ is rejected with an actual value of the test statistic, 52.1204 and 95% and 90% critical values of 34.9100 and 32.0030 respectively. The analysis proceeds by testing $r \leq 1$ against $r \geq 2$. The test statistic obtained is 13.2057 whereas the 95% and 90% critical values are and 17.8520 respectively. Thus using the trace test it is concluded that the number of cointegrating vectors is 1.

For the period 88Q1-94Q1, using the trace statistic, $r=0$ against $r \geq 1$ is rejected with a test statistic value of 52.1204 against 95% and 90% critical values of 34.91 and 32.0030. Continuing with $r \leq 1$ against $r \geq 2$, $r \leq 1$ cannot be rejected with a test statistic value of 13.2057 and 95% and 90% critical values of 19.9640 and 17.8520. So, the trace statistic favors the existence of unique cointegrating vector, too.

For 88Q1-94Q2, $r=0$ is rejected against $r \geq 1$ with a test statistic value of 38.2979 against 95% and 90% critical values of 34.91 and 32.0030 and then $r \leq 1$ cannot be rejected against $r \geq 2$ with a test statistic value of 14.354 against 95% and 90% critical values of 19.9640 and 17.8520. So, it is concluded that there is one cointegrating vector.

To sum up, for each of the periods of study, it is concluded that there is a unique cointegrating vector according to both the maximal eigenvalue and the trace test statistics, with the inclusion of the crisis quarters to the period 88Q1-93Q4, a fall in the level of the actual test statistics for the period 88Q1-94Q2 is observed which makes rejection of the hypothesis $r=0$ relatively hard.

The estimated β matrices (the cointegrating relationships) obtained by assuming no trend in model (1) are given in Tables A9, B9 and C9 with the coefficient of employment normalised to 1. These relationships can be written in the form:

For 88Q1-93Q4: $0.0079907 + 0.68282Y - 0.49524W - L = \varepsilon_1$

For 88Q1-94Q1: $0.0023738 + 1.0262Y - 0.59646W - L = \varepsilon_2$

For 88Q1-94Q2: $-0.017595 + 0.65705Y - 0.4779W - L = \varepsilon_3$

$\varepsilon_i, \quad i = 1,2,3$ is the vector of I(0) residuals.

The corresponding adjustment matrices (α) are given in Tables A10, B10 and C10 and the long run matrices Π in Tables A11, B11 and C11.

B. TESTING FOR COINTEGRATION UNDER THE ASSUMPTION OF LINEAR DETERMINISTIC TRENDS IN VARIABLES AND THE DATA GENERATING PROCESS

In the second case, model (1) is estimated subject to $H(r) = \Pi = \alpha\beta'$ where α and β are mxr matrices assuming that the variables in X as well as the DGP have linear deterministic trends.

i)Testing Through the Maximal Eigenvalue Test statistic:

The tests based on the maximal eigenvalue of the stochastic matrix are given in Tables A12, B12 and C12.

For 88Q1-93Q4, the null $r=0$ against the alternative $r=1$ is rejected with an actual value of the statistic 25.4076 and corresponding 95 % and 90 % critical values of 20.9670 and 18.5980. When proceeded to testing $r \leq 1$ against $r=2$, the actual statistic is 6.8234 and 95 % and 90 % critical values are 14.0690 and 12.0710. Thus, the null $r \leq 1$ cannot be rejected and we conclude that there is a unique cointegrating vector.

For 88Q1-94Q1; as reported in table B16, $r=0$ is rejected against the alternative $r=1$ with an actual test statistic of 34.4785 and 95 % and 90 % critical values of 20.9670 and 18.5980. $r \leq 1$ cannot be rejected against $r=2$ with an actual test statistic of 7.0101 and 95 % and 90 % critical values are 14.0690 and 12.0710 and thus a unique cointegrating vector is agreed..

For 88Q1-94Q2; with the maximal eigenvalue test as reported in Table C12, again a unique cointegrating vector is agreed upon rejecting $r=0$ against the alternative $r=1$ (with an actual test statistic of 22.3887 and 95 % and 90 % critical values of 20.9670 and 18.5980) and failing to reject $r \leq 1$ against $r=2$ (with a test statistic value of 7.7125 and 95 % and 90 % critical values are 14.0690 and 12.0710.

ii) Testing Through the Trace Test Statistic

If the trace test is used;

For 88Q1-93Q4, results are given in Tables A13. Firstly $r=0$ against $r \geq 1$ is tested and rejected with an actual statistic value of 37.1075 against 95 % and 90 % critical values of 29.68 and 26.7850. Then $r \leq 1$ is tested against $r \geq 2$ and we fail to reject $r \leq 1$ with an actual statistic value of 11.6999 and 95 % and 90 % critical values of 15.41 and 13.3250.

For 88Q1-94Q1, as given in table B13, $r=0$ is rejected against the alternative $r \geq 1$ with an actual test statistic of 42.4974 and 95 % and 90 % critical values of 29.68 and 26.7850. $r \leq 1$ cannot be rejected against $r \geq 2$ with an actual test statistic of 7.0189 and 95 % and 90 % critical values are 15.41 and 13.325. Thus a unique cointegrating vector is agreed upon.

For 88Q1-94Q2, as given in table C13, upon rejecting $r=0$ against $r \geq 1$ (with an actual test statistic of 32.1963 and 95 % and 90 % critical values of 29.68 and 26.7850) and failing to reject $r \leq 1$ against $r=2$ (with a test statistic value of 9.8076 and 95 % and 90 % critical values are 15.41 and 13.325, it is decided that there is unique cointegrating vector.

Tables A14, B14 and C14 give the cointegrating vectors (β matrices); tables A15, B15, C15 the adjustment matrices(α matrices) and tables A16, B16 and C16 give the long run matrices (Π). The cointegrating relation obtained can be expressed as :

For 88Q1-93Q4: $-L-0.49920W+0.69959Y=\gamma_1$

For 88Q1-94Q1 $:-L-0.59001W+1.0063Y=\gamma_2$

For 88Q1-94Q2: $-L-0.46601W+0.62177Y=\gamma_3$

where γ_i $i=1,2,3$ are I(0) residuals.

Finally $r=1$ is agreed upon under both of the assumptions (the zero trend and trended variables & trend in DGP assumption) and using both the maximal eigenvalue and the trace test statistics.

When the cointegrating relationships obtained under the two cases are examined, and if the period 88Q1-93Q4 is taken to represent the long run behavior of the labor market, a change in the long run coefficients of real wages and output is observed with the introduction of a shock into the system (the economic crisis). For the period 88Q1-94Q1, the sensitivity of employment to both output and real wages have increased but for the period 88Q1-94Q2 which includes the 5 April package, it is interesting to see that the coefficients of output and real wages have fallen down, becoming slightly less than those of the period 88Q1-93Q4.

In the next step, weak exogeneity tests for the real wage rate and output variables will be carried out and using the cointegrating relationships of non trended case (since it is found out to give slightly better fits), short run models for the three different periods including an error correction term for the demand for labor is investigated.

C. THE SHORT RUN MODELS

Before searching for short run relationships between the level of employment, real wages and output, whether the real wage rate and output can be assumed as weakly exogenous for the long run parameters of interest will be tested by restricting the α matrix using the method described in chapter 3.

The hypothesis α_2 *and* $\alpha_3=0$ will be tested agains the unrestricted α matrices. If this hypothesis is accepted, single equation estimation of α and β would be legitimate. The likelihood ratio tests derived using the method outlined in Chapter 3 give the following results:

For 1988 Quarter1 - 1993 Quarter4: $\chi^2_{(2)}=18.84$, $signif=0.00$

For 1988 Quarter1 - 1994 Quarter1: $\chi^2_{(2)}=17.69$ $signif=0.00$

For 1988 Quarter1 - 1994 Quarter2: $\chi^2_{(2)}=10.13$ $signif=0.01$

The p-value of the hypothesis is very low so since the real wage and output cannot be assumed as weakly exogenous for the long run parameters of interest, neither of these two variables can be dropped from the cointegrating relationship.

Since the regressors are not weakly exogenous for the dependent variable, the short run models of the behavior of the demand for labor have to be handled cautiously keeping in mind that both the period of study is relatively short and biases due to simultaneity may exist.

In choosing among various regressions which will represent the short run behavior of the system, importance is given not only to the significance of included variables but also to their coefficients' consistency with theory and the results of the diagnostic tests performed which will be described. Various OLS regressions of the dependent variable DL on variables DW, DY, their lags and seasonal dummies have been tested and the regression which explains the short run behavior best and performs well in the diagnostic tests is chosen and presented in Tables A17, B17 and C17. An explanation to the diagnostic tests used are given in Appendix D. In these regressions, the dependent variable is DL; the first difference of the employment series, and the regressors are:

$Q2$: ,quarterly dummy for the second quarter,
DY: first difference of output,
DW: the first difference of real wage,
$DW(-1)$: One period lag of the first difference of real wage,
$RES3(-1)$: One period lag of the residuals from the cointegrating relationship for the non-trended case and period 88Q1-93Q4, which is necessary for the system in converging to its long run equilibrium state,
$RES1(-1)$:One period lag of the residuals from the cointegrating relationship for the non-trended case and period 88Q1-94Q1,
$RES1P(-2)$: Two period lag of the residuals from the cointegrating relationship for the non-trended case and period 88Q1-94Q2.

$$DUM94(t) = \begin{cases} 1 & for \quad t = 94Q1 \\ 2 & for \quad t = 94Q2 \\ 0 & otherwise \end{cases}$$

As stated before, these OLS regressions yields favorable results to various diagnostic tests carried out at the 10 % significance level. The diagnostic test results give the test statistic values and corresponding probability values which are presented in Table A18, B18 and C18.

If the short run models for each period are examined:

For 88Q1-93Q4; a coefficient of 0.20947 and -0.15179 is observed for the first difference of output and real wage rate respectively and the coefficients of the dummy variable corresponding to quarter 2 and the error correction term are 0.035403 and -0.28161.

For 88Q1-94Q1; the coefficient of the first difference of output rises to 0.29862 while the absolute value of the coefficient of the first difference of the real wage rate to 0.067620. The quarterly dummy variable's coefficient falls to 0.030733 and the cointegrating relationship gains more weight and significance with a coefficient of -0.39922.

For 88Q1-94Q2; the coefficient of the first difference of output is 0.23921 a value in between those obtained for 88Q1-93Q4 and 88Q1-94Q1, the absolute value of the coefficient of the one period lag of the first difference of the real wage rate 0.11222, and the coefficient of the cointegrating relationship is -0.19738. In this model, a significant dummy variable representing the increased effect of the crisis with a value of 1 in 94Q1 and 2 in 94Q2 is very significant for 88Q1-94Q1 while it was not found to be significant in the various OLS regressions carried out for 88Q1-94Q1. So, it can be concluded that once the effects of the crisis started to be observed in the labor market, it gained pace and its effects became severe over time.

When considered as a whole, the short run models yield results attributable to the sample characteristics of the period under study due to the economic crisis of 1994 and like most of the systems, the labor demand function might exhibit deviations from the long run characteristics and behavior in the short run.

However, the existence of theory consistent long run relationships implying that employment is inversely related to real wages while it is positively related to output is very important since it guarantees a long run equilibrium among the demand for labor, real wages and output.

CHAPTER 5

CONCLUSION

In this study, the existence of long run relationships between employment, real wages and output in the Turkish manufacturing sector is tested using an error correction mechanism and Johansen's Maximum Likelihood procedure applied to three data periods:

1)1988 quarter 1-1993 quarter 4
2)1988 quarter 1-1994 quarter 1
3)1988 quarter 1-1994 quarter 2

and under two different assumptions for each period which are:

i) assumption of no deterministic trend in the VAR to be estimated

ii) assumption of linear deterministic trends in the model and the data generating process.

Testing for cointegration is carried out by considering both the maximal eigenvalue and the trace test statistics

The labor demand function to be estimated is specified as a function of output and real wages since demand constraints are assumed to be binding in the labor market due to the existence of excess supply.

Application of Johansen's procedure yields unique cointegrating relationships among the variables of interest for each period which are then used to build short run models for employment. Upon observing that the cointegrating vectors obtained by assumption (i) give better results, it is useful to report them:

For 88Q1-93Q4: $0.0079907+0.68282Y-0.49524W-L=\varepsilon_1$

For 88Q1-94Q1: $0.0023738+1.0262Y-0.59646W-L=\varepsilon_2$

For 88Q1-94Q2: $-0.017595+0.65705Y-0.4779W-L=\varepsilon_3$

where Y, L and W are output, employment and real wage series and Epsilon is the vector of I(0) residuals. These relationships are consistent with the theory regarding the signs and magnitudes of the coefficients. The cointegrating vectors of periods 1988Q1- 1993Q4 and 1988Q1-1994Q2 are similar whereas that of 1988Q1- 1994Q1 has higher coefficients of real wages and output in absolute terms. Based on the likelihood ratio tests of restrictions on the long run adjustment matrix it is found out that the real wage rate and output cannot be assumed as weakly exogenous for the demand for labor for the long run parameters of interest, and thus cannot be dropped from the cointegrating relationship.

Using the residuals of the above relationships (taking them as error correction terms), several short run models explaining the demand for labor are tested separately for each period. Among various models, the choice criteria were: significance and good fit of included regressors as well as coefficients' consistency with theory and the model's performance in the diagnostic tests carried out to test serial correlation, heteroskedasticity and normality of residuals an, functional form misspecification. The models chosen among OLS regressions yields acceptable results in all the diagnostic tests.

The short run models for 1988Q1-1993Q4 and 1988Q1-1994Q1 have the same explanatory variables (first difference of real wage and output, a dummy variable for quarter 2, and residuals of the cointegrating vector for the relevant period of study obtained under assumption (i)). However, in 1988Q1-1994Q2, a significant dummy variable representing the effects of the economic crisis on the labor market enters into the equation.

When the short run models for the demand for labor are considered -bearing in mind that the real wage rate and output cannot be assumed as weakly exogenous for the long run parameters of interest- they are consistent with theory but sensitive to the sample characteristics of the period under study and it is natural to observe deviations from the long run behavior in the short run.

The most important finding of this study is the existence of a long run relationship consistent with theory since it guarantees a long run equilibrium among the demand for labor, real wages and output. However it should be kept in mind that the estimated values are not at all representative of those which may be found in other settings or at higher levels of aggregation since labor demand elasticities are influenced by production and product market characteristics which vary among the sectors of the economy.

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APPENDICES

APPENDIX A

1988 QUARTER 1 - 1993 QUARTER 4

I. UNIT ROOT TESTS

TABLE 1: FOR VARIABLE W (LOG OF REAL WAGE)

			Without Trend		With Trend	
Statistic	Sample	Observation	Actual statistic	Critical Value (*)	Actual statistic	Critical Value (*)
DF	88Q2-93Q4	23	-1.0042	-2.9970	-1.7315	-3.6219
ADF(1)	88Q3-93Q4	22	-1.1948	-3.0039	-1.4210	-3.6331
ADF(2)	88Q4-93Q4	21	-1.4876	-3.0115	-.78842	-3.6454
ADF(3)	89Q1-93Q4	20	-1.3849	-3.0199	-.49163	-3.6592
ADF(4)	89Q2-93Q4	19	-1.5666	-3.0294	-.76323	-3.6746

(*) 95 % critical values.

TABLE 2: FOR VARIABLE L (LOG OF EMPLOYMENT)

			Without Trend		With Trend	
Statistic	Sample	Observation	Actual statistic	Critical Value (*)	Actual statistic	Critical Value (*)
DF	88Q2-93Q4	23	-0.80922	-2.9970	-1.6504	-3.6219
ADF(1)	88Q3-93Q4	22	-1.2050	-3.0039	-1.5650	-3.6331
ADF(2)	88Q4-93Q4	21	-1.1449	-3.0115	-1.3644	-3.6454
ADF(3)	89Q1-93Q4	20	-0.85225	-3.0199	-1.2560	-3.6592
ADF(4)	89Q2-93Q4	19	-1.2354	-3.0294	-4.7387	-3.6746

(*) 95 % critical values.

TABLE 3: FOR VARIABLE Y (LOG OF OUTPUT)

			Without Trend		With Trend	
Statistic	Sample	Observation	Actual statistic	Critical Value (*)	Actual statistic	Critical Value (*)
DF	88Q2-93Q4	23	-1.1681	-2.9970	-4.4119	-3.6219
ADF(1)	88Q3-93Q4	22	-.93249	-3.0039	-5.1360	-3.6331
ADF(2)	88Q4-93Q4	21	-.17574	-3.0115	-3.1886	-3.6454
ADF(3)	89Q1-93Q4	20	.12777	-3.0199	-1.6965	-3.6592
ADF(4)	89Q2-93Q4	19	-.73937	-3.0294	-2.3737	-3.6746

(*) 95 % critical values.

TABLE 4: FOR VARIABLE DL (FIRST DIFFERENCE OF L)

			Without Trend		With Trend	
Statistic	Sample	Observation	Actual statistic	Critical Value (*)	Actual statistic	Critical Value (*)
DF	88Q2-93Q4	23	-4.0919	-3.0039	-4.0075	-3.6331
ADF(1)	88Q3-93Q4	22	-3.1475	-3.0115	-3.0977	-3.6454
ADF(2)	88Q4-93Q4	21	-2.6521	-3.0199	-2.5752	-3.6592
ADF(3)	89Q1-93Q4	20	-0.96098	-3.0294	-0.91855	-3.6746
ADF(4)	89Q2-93Q4	19	-1.5664	-3.0401	-1.4113	-3.6921

(*) 95 % critical values.

TABLE 5: FOR VARIABLE DY (FIRST DIFFERENCE OF Y)

			Without Trend		With Trend	
Statistic	Sample	Observation	Actual statistic	Critical Value (*)	Actual statistic	Critical Value (*)
DF	88Q2-93Q4	2 23	-5.8401	-3.0039	-5.7138	-3.6331
ADF(1)	88Q3-93Q4	22	-6.5651	-3.0115	-6.4324	-3.6454
ADF(2)	88Q4-93Q4	21	-6.0676	-3.0199	-5.8974	-3.6592
ADF(3)	89Q1-93Q4	20	-3.3100	-3.0294	-3.2079	-3.6746
ADF(4)	89Q2-93Q4	19	-2.1000	-3.0401	-2.0076	-3.6921

(*) 95 % critical values.

TABLE 6: FOR VARIABLE DW (FIRST DIFFERENCE OF W)

Statistic	Sample	Observation	Without Trend: Actual statistic	Without Trend: Critical Value (*)	With Trend: Actual statistic	With Trend: Critical Value (*)
DF	88Q2-93Q4	23	-5.1210	-3.0039	-5.1583	-3.6331
ADF(1)	88Q3-93Q4	22	-4.1648	-3.0115	-4.3973	-3.6454
ADF(2)	88Q4-93Q4	21	-3.0716	-3.0199	-3.3523	-3.6592
ADF(3)	89Q1-93Q4	20	-1.9010	-3.0294	-2.3351	-3.6746
ADF(4)	89Q2-93Q4	19	-1.2765	-3.0401	-1.8685	-3.6921

(*) 95 % critical values.

II.JOHANSEN MAXIMUM LIKELIHOOD PROCEDURE (NON-TRENDED CASE)

COINTEGRATION LIKELIHOOD RATIO TESTS :

MAXIMUM LAG IN THE VECTOR AUTOREGRESSION MODEL (k) = 4.

VARIABLES INCLUDED IN THE COINTEGRATING VECTOR:
L : LOG OF EMPLOYMENT
W : LOG OF REAL WAGE
Y : LOG OF OUTPUT
INTERCEPT : INTERCEPT TERM

LIST OF EIGENVALUES IN DESCENDING ORDER:
.85710
.38238
.16346
.0000

TABLE 7: TABLE FOR THE DETERMINATION OF NUMBER OF COINTEGRATING VECTORS (r)

(BASED ON THE MAXIMAL EIGENVALUE OF THE STOCHASTIC MATRIX)

Null	Alternative	Statistic	95% critical value	90% critical value
r =0	r = 1	38.9124	22.0020	19.7660
r <= 1	r = 2	9.6377	15.6720	13.7520
r <= 2	r = 3	3.5697	9.2430	7.5250

TABLE 8: TABLE FOR THE DETERMINATION OF NUMBER OF COINTEGRATING VECTORS (r)

(BASED ON THE TRACE OF THE STOCHASTIC MATRIX)

Null	Alternative	Statistic	95% critical value	90% critical value
r =0	r > 1	52.1204	34.9100	32.0030
r <= 1	r > 2	13.2057	19.9640	17.8520
r <= 2	r > 3	3.5693	9.2430	7.5250

TABLE 9: ESTIMATED COINTEGRATED VECTORS (NORMALISED IN BRACKETS)*

β VECTOR

	Vector 1
L	10.5229 (-1.0000)
W	6.2765 (-0.59646)
Y	-10.7983 (1.0262)
INTERCEPT	-0.24980 (0.023738)

(*) The coefficient of L is set to -1.0000 in the linear combination of L,Y,W and intercept.

TABLE 10: ESTIMATED ADJUSTMENT MATRIX (NORMALISED IN BRACKETS)*

α MATRIX

	Vector 1
L	-0.10439 (1.0985)
W	0.020011 (-0.21057)
Y	-0.092619 (0.97462)

TABLE 11: ESTIMATED LONG RUN MATRIX

$$\Pi = \alpha\beta'$$

	L	W	Y	INTERCEPT
L	-1.0984	-0.65518	1.1272	0.026075
W	0.21057	0.12560	-0.21608	-0.0049986
Y	-0.97462	-0.58132	1.0001	0.023136

III . JOHANSEN MAXIMUM LIKELIHOOD PROCEDURE (TRENDED CASE, WITH TREND IN THE DATA GENERATING PROCESS)

COINTEGRATION LIKELIHOOD RATIO TEST:

LIST OF EIGENVALUES IN DESCENDING ORDER:
.83033
.29567
.4387 E-3

TABLE 12: TABLE FOR THE DETERMINATION OF NUMBER OF COINTEGRATING VECTORS (r)

(BASED ON THE MAXIMAL EIGENVALUE OF THE STOCHASTIC MATRIX)

Null	Alternative	Statistic	95% critical value	90% critical value
r =0	r = 1	35.4785	20.9670	18.5980
r <= 1	r = 2	7.0101	14.0690	12.0710
r <= 2	r = 3	0.0087757	3.7620	2.6870

TABLE 13: TABLE FOR THE DETERMINATION OF NUMBER OF COINTEGRATING VECTORS (r)

(BASED ON THE TRACE OF THE STOCHASTIC MATRIX)

Null	Alternative	Statistic	95% critical value	90% critical value
r =0	r > 1	42.4974	23.6800	26.7850
r <= 1	r > 2	7.0189	15.4100	13.3250
r <= 2	r > 3	0.0087757	3.7620	2.6870

TABLE 14: ESTIMATED COINTEGRATED VECTORS (NORMALISED IN BRACKETS)*

β MATRIX

	Vector 1
L	-11.7733 (-1.0000)
W	-6.9463 (-0.59001)
Y	11.8479 (1.0063)

(*) The coefficient of L is set to -1.0000 in the linear combination of L,Y,W and intercept.

TABLE 15: ESTIMATED ADJUSTMENT MATRIX (NORMALISED IN BRACKETS)*

α MATRIX

	Vector 1
L	0.10353 (1.2189)
W	-0.058357 (-0.68706)
Y	0.077246 (0.90945)

TABLE 16: ESTIMATED LONG RUN MATRIX

$$\Pi = \alpha\beta'$$

	L	W	Y
L	-1.2189	-0.71913	1.2266
W	0.68706	0.40537	-0.69141
Y	-0.90945	-0.53658	0.91521

SELECTED MODEL

TABLE 17: OLS ESTIMATION

Using the cointegrating vector of non-trended case

Dependent Variable: DL

Regressor	Coefficient	T-Ratio [Probability]
DY	0.20947	2.2305 [0.041]
DW	-0.15179	-2.4665 [0.026]
Q2	0.035403	2.7844 [0.014]
RES3(-1)	-0.28161	-3.7483 [0.002]

R-Squared	0.67990
R-Bar-Squared	0.61588
Residual Sum of Squares	0.0071196
S.D. of Dependent Variable	0.035152
DW-statistic	1.7290
F-Statistic F(3,15)	10.6201 [0.001]
S.E. of Regression	0.02178
Max. of Log-likelihood	47.988

TABLE 18: DIAGNOSTIC TESTS

Test Statistics	LM Version	F Version
A.Serial Correlation	CHI-SQ(4) = 5.7013 [0.223]	F(4,11) = 1.1790 [0.372]
B. Functional Form	CHI-SQ(1) = 1.4722 [0.225]	F(1,14) = 1.1759 [0.297]
C. Normality	CHI-SQ(2) = 0.14516 [0.930]	-
D.Heteroskedasticity	CHI-SQ(1) = 1.3897 [0.238]	F(1,17) = 1.3415 [0.263]

A. Lagrange Multiplier Test of serial correlation
B. Ramsey's RESET test using the square of the fitted values
C. Based on a test of skewness and kurtosis of residuals
D. Based on the regression of the squared residuals on squared fitted values.

APPENDIX B

1988 QUARTER 1 - 1994 QUARTER 1

I. UNIT ROOT TESTS

TABLE 1: FOR VARIABLE W (LOG OF REAL WAGE)

Statistic	Sample	Observation	Without Trend: Actual statistic	Without Trend: Critical Value (*)	With Trend: Actual statistic	With Trend: Critical Value (*)
DF	88Q2-94Q1	24	-1.2191	-2.9907	-1.2857	-3.6119
ADF(1)	88Q3-94Q1	23	-1.4145	-2.9970	-0.95685	-3.6219
ADF(2)	88Q4-94Q1	22	-1.7770	-3.0039	-0.39651	-3.6331
ADF(3)	88Q1-94Q1	21	-1.6483	-3.0115	-0.12584	-3.6454
ADF(4)	89Q2-94Q1	20	-1.8003	-3.0199	-0.21771	-3.6592

(*) 95 % critical values.

TABLE 2: FOR VARIABLE L (LOG OF EMPLOYMENT)

Statistic	Sample	Observation	Without Trend: Actual statistic	Without Trend: Critical Value (*)	With Trend: Actual statistic	With Trend: Critical Value (*)
DF	88Q2-94Q1	24	-0.59108	-2.9907	-1.9647	-3.6119
ADF(1)	88Q3-94Q1	23	-0.92042	-2.9970	-1.9205	-3.6219
ADF(2)	88Q4-94Q1	22	-0.89469	-3.0039	-1.6949	-3.6331
ADF(3)	88Q1-94Q1	21	-0.62413	-3.0115	-1.5031	-3.6454
ADF(4)	89Q2-94Q1	20	-0.98524	-3.0199	-5.1493	-3.6592

(*) 95 % critical values.

TABLE 3: FOR VARIABLE Y (LOG OF OUTPUT)

Statistic	Sample	Observation	Without Trend: Actual statistic	Without Trend: Critical Value (*)	With Trend: Actual statistic	With Trend: Critical Value (*)
DF	88Q2-94Q1	24	-1.9680	-2.9907	-4.5819	-3.6119
ADF(1)	88Q3-94Q1	23	-1.8045	-2.9970	-5.6665	-3.6219
ADF(2)	88Q4-94Q1	22	-1.1360	-3.0039	-4.0422	-3.6331
ADF(3)	88Q1-94Q1	21	-0.34007	-3.0115	-1.8635	-3.6454
ADF(4)	89Q2-94Q1	20	-1.2261	-3.0199	-2.5725	-3.6592

(*) 95 % critical values.

TABLE 4: FOR VARIABLE DL (FIRST DIFFERENCE OF L)

Statistic	Sample	Observation	Without Trend: Actual statistic	Without Trend: Critical Value (*)	With Trend: Actual statistic	With Trend: Critical Value (*)
DF	88Q3-94Q1	23	-4.4608	-2.9970	-4.3699	-3.6219
ADF(1)	88Q4-94Q1	22	-3.5019	-3.0039	-3.4377	-3.6331
ADF(2)	89Q1-94Q1	21	-3.0984	-3.0115	-3.0099	-3.6454
ADF(3)	89Q2-94Q1	20	-1.1978	-3.0199	-1.1562	-3.6592
ADF(4)	89Q3-94Q1	19	-1.8691	-3.0294	-1.7970	-3.6746

(*) 95 % critical values.

TABLE 5: FOR VARIABLE DY (FIRST DIFFERENCE OF Y)

Statistic	Sample	Observation	Without Trend: Actual statistic	Without Trend: Critical Value (*)	With Trend: Actual statistic	With Trend: Critical Value (*)
DF	88Q3-94Q1	23	-5.2707	-2.9970	-5.1085	-3.6219
ADF(1)	88Q4-94Q1	22	-5.9872	-3.0039	-5.7689	-3.6331
ADF(2)	89Q1-94Q1	21	-7.2809	-3.0115	-6.9925	-3.6454
ADF(3)	89Q2-94Q1	20	-3.6446	-3.0199	-3.5266	-3.6592
ADF(4)	89Q3-94Q1	19	-2.4944	-3.0294	-2.4901	-3.6746

(*) 95 % critical values.

TABLE 6: FOR VARIABLE DW (FIRST DIFFERENCE OF W)

			Without Trend		With Trend	
Statistic	Sample	Observation	Actual statistic	Critical Value (*)	Actual statistic	Critical Value (*)
DF	88Q3-94Q1	23	-5.0832	-2.9970	-5.2404	-3.6219
ADF(1)	88Q4-94Q1	22	-3.8761	-3.0039	-4.3536	-3.6331
ADF(2)	89Q1-94Q1	21	-2.7599	-3.0115	-3.2741	-3.6454
ADF(3)	89Q2-94Q1	20	-1.6564	-3.0199	-2.3180	-3.6592
ADF(4)	89Q3-94Q1	19	-1.0347	-3.0294	-1.8848	-3.6746

(*) 95 % critical values.

II. JOHANSEN MAXIMUM -LIKELIHOOD PROCEDURE (NON-TRENDED CASE)

COINTEGRATION LIKELIHOOD RATIO TESTS:

MAXIMUM LAG IN THE VECTOR AUTOREGRESSION MODEL (k) = 4.

VARIABLES INCLUDED IN THE COINTEGRATING VECTOR:
L : LOG OF EMPLOYMENT
W : LOG OF REAL WAGE
Y : LOG OF OUTPUT
INTERCEPT : INTERCEPT TERM

LIST OF EIGENVALUES IN DESCENDING ORDER:
0.70794
0.34635
0.22646
0.00000

TABLE 7: TABLE FOR THE DETERMINATION OF NUMBER OF COINTEGRATING VECTORS (r)

(BASED ON THE MAXIMAL EIGENVALUE OF THE STOCHASTIC MATRIX)

Null	Alternative	Statistic	95% critical value	90% critical value
r =0	r = 1	25.8464	22.0020	19.7660
r <= 1	r = 2	8.9288	15.6720	13.7520
r <= 2	r = 3	5.3923	9.2430	7.5250

TABLE 8: TABLE FOR THE DETERMINATION OF NUMBER OF COINTEGRATING VECTORS (r)

(BASED ON THE TRACE OF THE STOCHASTIC MATRIX)

Null	Alternative	Statistic	95% critical value	90% critical value
r =0	r > 1	40.1675	34.9100	32.0030
r <= 1	r > 2	14.3211	19.9640	17.8520
r <= 2	r > 3	5.3923	9.2430	7.5250

TABLE 9: ESTIMATED COINTEGRATED VECTORS (NORMALISED IN BRACKETS)*

β VECTOR

	Vector1
L	10.8785 (-1.0000)
W	-5.3875 (-0.49524)
Y	7.4280 (0.68282)
INTERCEPT	0.086926 (0.0079907)

(*) The coefficient of L is set to -1.0000 in the linear combination of L,Y,W and intercept.

TABLE 10: ESTIMATED ADJUSTMENT MATRIX (NORMALISED IN BRACKETS)*

α MATRIX

	Vector1
L	0.10375 (1.1286)
W	-0.11285 (-1.2276)
Y	0.074034 (0.80538)

TABLE 11: ESTIMATED LONG RUN MATRIX

$$\Pi = \alpha\beta'$$

	L	W	Y	INTERCEPT
L	-1.1286	-0.55894	0.77065	0.0090185
W	1.2276	0.60795	-0.83822	-0.0098093
Y	-0.80538	-0.39885	0.54992	0.0064355

III. JOHANSEN MAXIMUM-LIKELIHOOD PROCEDURE (TRENDED CASE, WITH TREND IN THE DATA GENERATING PROCESS)

COINTEGRATION LIKELIHOOD RATIO TESTS:

LIST OF EIGENVALUES IN DESCENDING ORDER:
0.70177
0.27742
0.20723

TABLE 12: TABLE FOR THE DETERMINATION OF NUMBER OF COINTEGRATING VECTORS (r)

(BASED ON THE MAXIMAL EIGENVALUE OF THE STOCHASTIC MATRIX)

Null	Alternative	Statistic	95% critical value	90% critical value
r =0	r = 1	25.4076	20.9670	18.5980
r <= 1	r = 2	6.8234	14.0690	12.0710
r <= 2	r = 3	4.8765	3.7620	2.6870

TABLE 13: TABLE FOR THE DETERMINATION OF NUMBER OF COINTEGRATING VECTORS (r)

(BASED ON THE TRACE OF THE STOCHASTIC MATRIX)

Null	Alternative	Statistic	95% critical value	90% critical value
r =0	r > 1	37.1075	29.6800	26.7850
r <= 1	r > 2	11.6999	15.4100	13.3250
r <= 2	r > 3	4.8765	3.7620	2.6870

TABLE 14: ESTIMATED COINTEGRATED VECTORS (NORMALISED IN BRACKETS)*

β MATRIX

	Vector1
L	11.0991 (-1.0000)
W	5.5407 (-0.49920)
Y	-7.7648 (0.69959)

(*) The coefficient of L is set to -1.0000 in the linear combination of L,Y,W and intercept.

TABLE 15:: ESTIMATED ADJUSTMENT MATRIX (NORMALISED IN BRACKETS)*

α MATRIX

	Vector1
L	-0.10029 (1.1131)
W	0.12670 (-1.4063)
Y	-0.064729 (0.71844)

TABLE 16: ESTIMATED LONG RUN MATRIX

$$\Pi = \alpha\beta'$$

	L	W	Y
L	-1.1131	-0.55566	0.77871
W	1.4063	0.70200	-0.98379
Y	-0.71844	-0.35865	0.50261

TABLE 17: OLS ESTIMATION

Using the cointegrating vector of non-trended case

Dependent Variable: DL

Regressor	Coefficient	T-Ratio [Probability]
DY	0.29862	4.8331 [0.000]
DW	-0.067620	-1.4376 [0.170]
Q2	0.030733	3.0472 [0.008]
RES1(-1)	-0.39922	-5.4952 [0.000]

R-Squared	0.77184
R-Bar-Squared	0.72905
Residual Sum of Squares	0.0054171
S.D. of Dependent Variable	0.035349
DW-statistic	1.8605
F-Statistic F(3,16)	18.0416 [0.000]
S.E. of Regression	0.01840
Max. of Log-likelihood	53.760

TABLE 18: DIAGNOSTIC TESTS

Test Statistics	LM Version	F Version
A.Serial Correlation	CHI-SQ(4) = 2.9199 [0.571]	F(4,12) = 0.51285 [0.728]
B. Functional Form	CHI-SQ(1) = 2.4487 [0.118]	F(1,15) = 2.0927 [0.169]
C. Normality	CHI-SQ(2) = 1.0690 [0.586]	-
D.Heteroskedasticity	CHI-SQ(1) = 1.9464 [0.163]	F(1,18) = 1.9406 [0.181]

A. Lagrange Multiplier Test of serial correlation
B. Ramsey's RESET test using the square of the fitted values
C. Based on a test of skewness and kurtosis of residuals
D. Based on the regression of the squared residuals on squared fitted values.

APPENDIX C

1988 QUARTER1 - 1994 QUARTER2

I. UNIT ROOT TESTS

TABLE 1: FOR VARIABLE W (LOG OF REAL WAGE)

			Without Trend		With Trend	
Statistic	Sample	Observation	Actual statistic	Critical Value (*)	Actual statistic	Critical Value (*)
DF	88Q1-94Q2	25	-1.5702	-2.9850	0.41999	-3.6027
ADF(1)	88Q2-94Q2	24	-1.6925	-2.9907	0.58249	-3.6119
ADF(2)	88Q3-94Q2	23	-1.8893	-2.9970	1.1490	-3.6219
ADF(3)	89Q1-94Q2	22	-1.6592	-3.0039	1.0444	-3.6331
ADF(4)	89Q2-94Q2	21	-1.6827	-3.0115	0.85576	-3.6454

(*) 95 % critical values.

TABLE 2: FOR VARIABLE L (LOG OF EMPLOYMENT)

			Without Trend		With Trend	
Statistic	Sample	Observation	Actual statistic	Critical Value (*)	Actual statistic	Critical Value (*)
DF	88Q1-94Q2	25	-0.32510	-2.9850	-2.1170	-3.6027
ADF(1)	88Q2-94Q2	24	-0.70538	-2.9907	-2.1591	-3.6119
ADF(2)	88Q3-94Q2	23	-0.68057	-2.9970	-1.8768	-3.6219
ADF(3)	89Q1-94Q2	22	-0.43566	-3.0039	-1.6655	-3.6331
ADF(4)	89Q2-94Q2	21	-0.56622	-3.0115	-5.5438	-3.6454

(*) 95 % critical values.

TABLE 3: FOR VARIABLE Y (LOG OF OUTPUT)

Statistic	Sample	Observation	Without Trend Actual statistic	Without Trend Critical Value (*)	With Trend Actual statistic	With Trend Critical Value (*)
DF	88Q1-94Q2	25	-1.9056	-2.9850	-4.5400	-3.6027
ADF(1)	88Q2-94Q2	24	-1.7458	-2.9907	-5.7212	-3.6119
ADF(2)	88Q3-94Q2	23	-1.1963	-2.9970	-4.0596	-3.6219
ADF(3)	89Q1-94Q2	22	-0.73638	-3.0039	-1.9528	-3.6331
ADF(4)	89Q2-94Q2	21	-1.6410	-3.0115	-2.5688	-3.6454

(*) 95 % critical values.

TABLE 4: FOR VARIABLE DL (FIRST DIFFERENCE OF L)

Statistic	Sample	Observation	Without Trend Actual statistic	Without Trend Critical Value (*)	With Trend Actual statistic	With Trend Critical Value (*)
DF	88Q3-94Q4	24	-4.4079	-2.9907	-4.3054	-3.6119
ADF(1)	88Q4-94Q4	23	-3.5632	-2.9970	-3.4702	-3.6219
ADF(2)	89Q1-94Q4	22	-3.2000	-3.0039	-3.0821	-3.6331
ADF(3)	89Q2-94Q4	21	-1.3751	-3.0115	-1.2897	-3.6454
ADF(4)	89Q3-94Q4	20	-2.0489	-3.0199	-1.9671	-3.6592

(*) 95 % critical values.

TABLE 5 : FOR VARIABLE DY (FIRST DIFFERENCE OF Y)

Statistic	Sample	Observation	Without Trend Actual statistic	Without Trend Critical Value (*)	With Trend Actual statistic	With Trend Critical Value (*)
DF	88Q3-94Q4	24	-6.1384	-2.9907	-6.0423	-3.6119
ADF(1)	88Q4-94Q4	23	-6.5044	-2.9970	-6.3897	-3.6219
ADF(2)	89Q1-94Q4	22	-7.3432	-3.0039	-7.1771	-3.6331
ADF(3)	89Q2-94Q4	21	-3.5424	-3.0115	-3.5105	-3.6454
ADF(4)	89Q3-94Q4	20	-2.4032	-3.0199	-2.4950	-3.6592

(*) 95 % critical values.

TABLE 6: FOR VARIABLE DW (FIRST DIFFERENCE OF W)

Statistic	Sample	Observation	Without Trend: Actual statistic	Without Trend: Critical Value (*)	With Trend: Actual statistic	With Trend: Critical Value (*)
DF	88Q3-94Q4	24	-3.2815	-2.9907	-3.7947	-3.6119
ADF(1)	88Q4-94Q4	23	-2.3464	-2.9970	-3.1402	-3.6219
ADF(2)	89Q1-94Q4	22	-1.0725	-3.0039	-1.9029	-3.6331
ADF(3)	89Q2-94Q4	21	-0.21799	-3.0115	-1.1526	-3.6454
ADF(4)	89Q3-94Q4	20	-0.046058	-3.0199	-1.0532	-3.6592

(*) 95 % critical values.

II .JOHANSEN MAXIMUM LIKELIHOOD PROCEDURE (NON-TRENDED CASE)

COINTEGRATION LIKELIHOOD RATIO TESTS:

MAXIMUM LAG IN THE VECTOR AUTOREGRESSION MODEL (k) = 4.

VARIABLES INCLUDED IN THE COINTEGRATING VECTOR:
L : LOG OF EMPLOYMENT
W : LOG OF REAL WAGE
Y : LOG OF OUTPUT
INTERCEPT : INTERCEPT TERM

LIST OF EIGENVALUES IN DESCENDING ORDER:
0.66323
0.32707
0.22612
0.00000

TABLE 7: TABLE FOR THE DETERMINATION OF NUMBER OF COINTEGRATING VECTORS (r)

(BASED ON THE MAXIMAL EIGENVALUE OF THE STOCHASTIC MATRIX)

Null	Alternative	Statistic	95% critical value	90% critical value
r =0	r = 1	23.9439	22.0020	19.7660
r <= 1	r = 2	8.7145	15.6720	13.7520
r <= 2	r = 3	5.6396	9.2430	7.5250

TABLE 8: TABLE FOR THE DETERMINATION OF NUMBER OF COINTEGRATING VECTORS (r)

(BASED ON THE TRACE OF THE STOCHASTIC MATRIX)

Null	Alternative	Statistic	95% critical value	90% critical value
r =0	r > 1	38.2979	34.9100	32.0030
r <= 1	r > 2	14.3540	19.9640	17.8520
r <= 2	r > 3	5.6396	9.2430	7.5250

TABLE 9: ESTIMATED COINTEGRATED VECTORS (NORMALISED İN BRACKETS)*

β VECTOR

	Vector1
L	10.3578 (-1.0000)
W	4.9505 (-0.47795)
Y	-6.8056 (0.65705)
INTERCEPT	0.18224 (-0.017595)

(*) The coefficient of L is set to -1.0000 in the linear combination of L,Y,W and intercept.

TABLE 10: ESTIMATED ADJUSTMENT MATRIX (NORMALISED IN BRACKETS)*

α MATRIX

	Vector1
L	-0.11624 (1.2039)
W	0.058217 (-0.60300)
Y	-0.058519 (0.60613)

TABLE 11: ESTIMATED LONG RUN MATRIX

$$\Pi = \alpha\beta'$$

	L	W	Y	INTERCEPT
L	-1.2039	-0.57542	0.79105	-0.021183
W	0.60300	0.28820	-0.39620	0.010610
Y	-0.60613	-0.28970	0.39826	-0.010665

III. JOHANSEN MAXIMUM-LIKELIHOOD PROCEDURE (TRENDED CASE, WITH TREND IN THE DATA GENERATING PROCESS)

COINTEGRATION LIKELIHOOD RATIO TESTS :

LIST OF EIGENVALUES IN DESCENDING ORDER:
0.63856
0.29571
0.090837

TABLE 12: TABLE FOR THE DETERMINATION OF NUMBER OF COINTEGRATING VECTORS (r)

(BASED ON THE MAXIMAL EIGENVALUE OF THE STOCHASTIC MATRIX)

Null	Alternative	Statistic	95% critical value	90% critical value
r =0	r = 1	22.3887	20.9670	18.5980
r <= 1	r = 2	7.7125	14.0690	12.0710
r <= 2	r = 3	2.0951	3.7620	2.6870

TABLE 13: TABLE FOR THE DETERMINATION OF NUMBER OF COINTEGRATING VECTORS (r)

(BASED ON THE TRACE OF THE STOCHASTIC MATRIX)

Null	Alternative	Statistic	95% critical value	90% critical value
r =0	r > 1	32.1963	29.6800	26.7850
r <= 1	r > 2	9.8076	15.4100	13.3250
r <= 2	r > 3	2.0951	3.7620	2.6870

TABLE 14: ESTIMATED COINTEGRATED VECTORS (NORMALISED IN BRACKETS)*

β MATRIX

	Vector1
L	10.9632 (-1.0000)
W	5.1089 (-0.46601)
Y	-6.8166 (0.62177)

(*) The coefficient of L is set to -1.0000 in the linear combination of L,Y,W and intercept.

TABLE 15: ESTIMATED ADJUSTMENT MATRIX (NORMALISED IN BRACKETS)*

α MATRIX

	Vector1
L	-0.11014 (1.2075)
W	0.12035 (-1.3195)
Y	-0.076536 (0.83908)

TABLE 16: ESTIMATED LONG RUN MATRIX

$$\Pi = \alpha\beta'$$

	L	W	Y
L	-1.2075	-0.56269	0.75077
W	1.3195	0.61488	-0.82041
Y	-0.83908	-0.39102	0.52172

TABLE 17

OLS ESTIMATION

Using the cointegrating vector of non-trended case

Dependent Variable: DL

Regressor	Coefficient	T-Ratio [Probability]
DY	0.23921	3.9348 [0.001]
DW(-1)	-0.11222	-2.0458 [0.058]
DUM94	-0.031338	-2.9016 [0.010]
RES1(-2)	-0.19738	-3.1868 [0.006]

WHERE 94Q1=1 94Q2=2 AND 0 OTHERWISE.

R-Squared	0.57507
R-Bar-Squared	0.49540
Residual Sum of Squares	0.0092156
S.D. of Dependent Variable	0.033785
DW-statistic	2.3868
F-Statistic F(3,16)	7.2179 [0.003]
S.E. of Regression	0.02400
Max. of Log-likelihood	48.447

TABLE 18: DIAGNOSTIC TESTS

Test Statistics	LM Version	F Version
A.Serial Correlation	CHI-SQ(4) = 1.9122 [0.752]	F(4,12) = 0.31715 [0.861]
B. Functional Form	CHI-SQ(1) = 0.12455 [0.724]	F(1,15) = 0.093999 [0.763]
C. Normality	CHI-SQ(2) = 0.96612 [0.617]	-
D.Heteroskedasticity	CHI-SQ(1) = 0.016866 [0.897]	F(1,18) = 0.015192 [0.903]

A. Lagrange Multiplier Test of serial correlation
B. Ramsey's RESET test using the square of the fitted values
C. Based on a test of skewness and kurtosis of residuals
D. Based on the regression of the squared residuals on squared fitted values.

APPENDIX D

TESTING FOR SERIAL CORRELATION

In testing for serial correlation, the null hypothesis is that the errors are non autocorrelated and the alternative is that they are autocorrelated of order 4 since the data is quarterly. The test used is "Godfrey's Test of Residual Serial Correlation" where LM version of the test statistic is computed by:

$$\text{(a)}\ \chi^2_{sc}(p) = n\left(\frac{e'_{OLS}W(W'M_xW)^{-1}W'e_{OLS}}{e'_{OLS}e_{OLS}}\right) \approx \chi^2_p,$$

where

$$M_x = I - X(X'X)^{-1}X'$$

$$e_{OLS} = y - x\hat{\beta}_{OLS} = (e_1, e_2, \ldots e_n)'$$

p: order of autocorrelation and
W matrix

$$W = \begin{matrix} 0 & 0 & \cdots & 0 \\ e_1 & 0 & \cdots & 0 \\ e_2 & e_1 & \cdots & \vdots \\ \vdots & \vdots & \vdots & e_{n-p-1} \\ e_{n-1} & e_{n-2} & \cdots & e_{n-p} \end{matrix}$$

The F version is given by:

$$\text{(b)}\ F(p) = \left(\frac{n-k-p}{p}\right)\left(\frac{\chi^2_{sc}(p)}{n-\chi^2_{sc}(p)}\right) \approx F_{p,n-k-p}$$

FUNCTIONAL FORM TEST

The functional form test is "Ramsey's RESET Test for Functional Form Misspecification" . The null tested is that the functional form is well specified and the alternative is that it is misspecified. The form of this test is as given in (a) and (b) but W is the square of the fitted values.

$$W = (\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n)'$$

TESTING FOR NORMALITY

Testing for normality is performed by the test proposed by Bera & Jarque, LM version of which is given by:

$$\chi_N^2(2) = n\left\{\mu_3^2/\left(6\mu_2^3\right) + (1/24)\left(\mu_4/\mu_2^2 - 3\right)^2\right\} + n\left\{3\mu_1^2/(2\mu_2) - \mu_3\mu_1/\mu_2^2\right\} \approx \chi^2(2)$$

where

$$\mu_j = \sum_{t=1}^{j} e_t^j / n, \quad j = 1,2,\ldots$$

TESTING FOR HETEROSKEDASTICITY

Heteroskedasticity is tested with a null hypothesis of homoskedasticity providing a LM test of $\gamma = 0$ in

$$E\left(u_t^2\right) = \sigma_t^2 = \sigma^2 + \gamma\left(x'\beta_t\right)^2$$

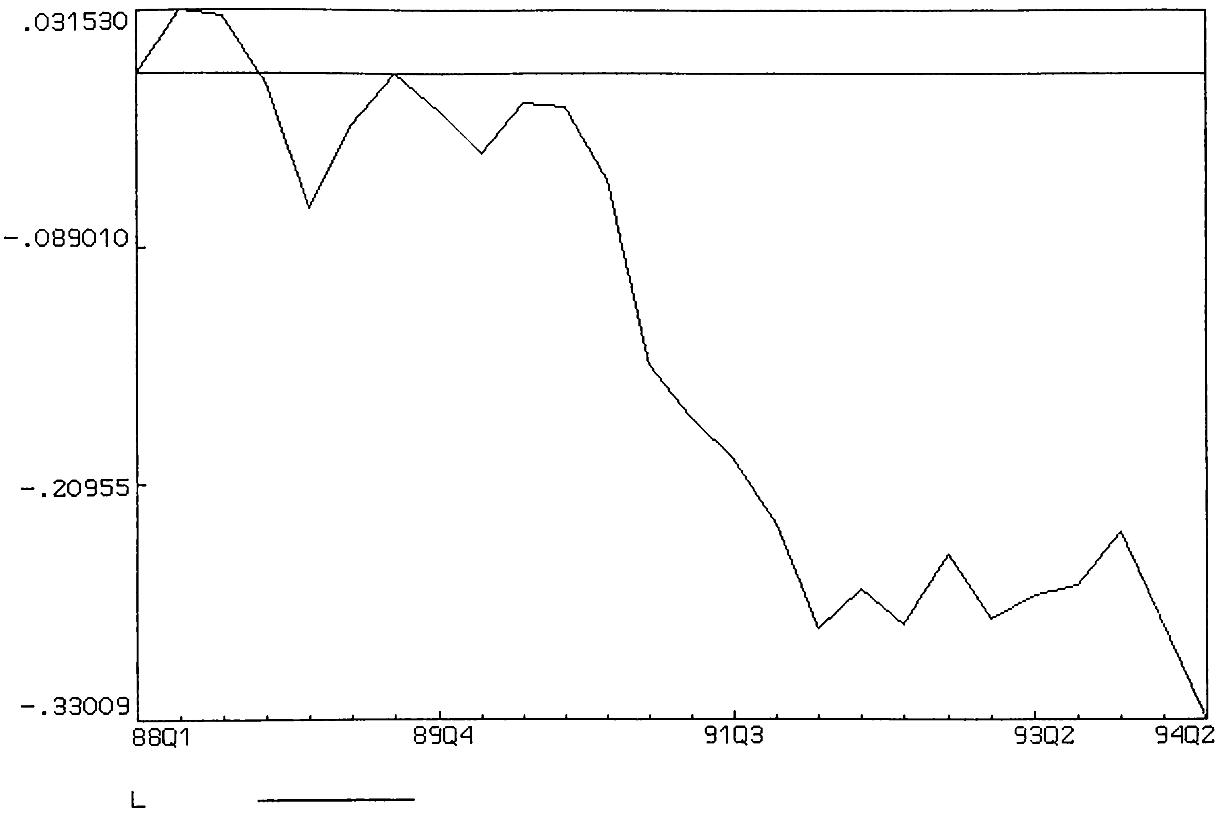
TABLE 19

	QUARTER	PRIVATE MANUFACTURING SECTOR: EMPLOYMENT INDEX	EMPLOYMENT INDEX 88Q1=1	LN (EMP. INDEX)	REAL WAGE INDEX	LN (REAL WAGE) INDEX	PRODUCTION INDEX	PROD. INDEX 1988=1	LN (PROD. INDEX
1988	1	112,4	1,00000	0,00000	1,00000	0,00000	110,2	1,00000	0,00000
	2	116,0	1,03203	0,03153	0,98949	−0,01057	106,6	0,96733	−0,03321
	3	115,6	1,02847	0,02807	0,97134	−0,02908	106,4	0,96552	−0,03509
	4	111,8	0,99466	−0,00535	1,08173	0,07856	114,0	1,03448	0,03390
1989	1	104,8	0,93238	−0,07001	1,11420	0,10814	103,8	0,94192	−0,05983
	2	109,5	0,97420	−0,02614	1,14667	0,13686	113,8	1,03267	0,03215
	3	112,4	1,00000	0,00000	1,20025	0,18253	120,6	1,09437	0,09018
	4	110,3	0,98132	−0,01886	1,36476	0,31098	127,9	1,16062	0,14895
1990	1	107,9	0,95996	−0,04086	1,46908	0,38464	122,0	1,10708	0,10172
	2	110,7	0,98488	−0,01524	1,51063	0,41252	123,2	1,11797	0,11151
	3	110,5	0,98310	−0,01705	1,65096	0,50136	133,4	1,21053	0,19106
	4	106,4	0,94662	−0,05486	1,57767	0,45595	141,3	1,28221	0,24859
1991	1	96,8	0,86121	−0,14942	2,31339	0,83871	114,6	1,03993	0,03915
	2	94,2	0,83808	−0,17664	2,44171	0,89270	127,1	1,15336	0,14268
	3	92,3	0,82117	−0,19702	2,35603	0,85698	142,7	1,29492	0,25845
	4	89,2	0,79359	−0,23118	2,28538	0,82653	145,7	1,32214	0,27925
1992	1	84,6	0,75267	−0,28413	2,43148	0,88850	131,7	1,19510	0,17823
	2	86,3	0,76779	−0,26423	2,56943	0,94368	132,1	1,19873	0,18126
	3	84,7	0,75356	−0,28295	2,44063	0,89225	146,6	1,33031	0,28541
	4	87,8	0,78114	−0,24700	2,40637	0,87812	149,6	1,35753	0,30567
1993	1	85,0	0,75623	−0,27941	2,76541	1,01719	133,6	1,21234	0,19255
	2	86,0	0,76512	−0,26772	2,84018	1,04387	154,3	1,40018	0,33660
	3	86,4	0,76868	−0,26308	2,61347	0,96068	163,3	1,48185	0,39329
	4	88,9	0,79093	−0,23455	2,68118	0,98626	167,2	1,51724	0,41689
1994	1	84,7	0,75356	−0,28295	2,54402	0,93375	137,1	1,24410	0,21841
	2	80,8	0,71886	−0,33009	1,76096	0,56586	143	1,29764	0,26055

GRAPHICS

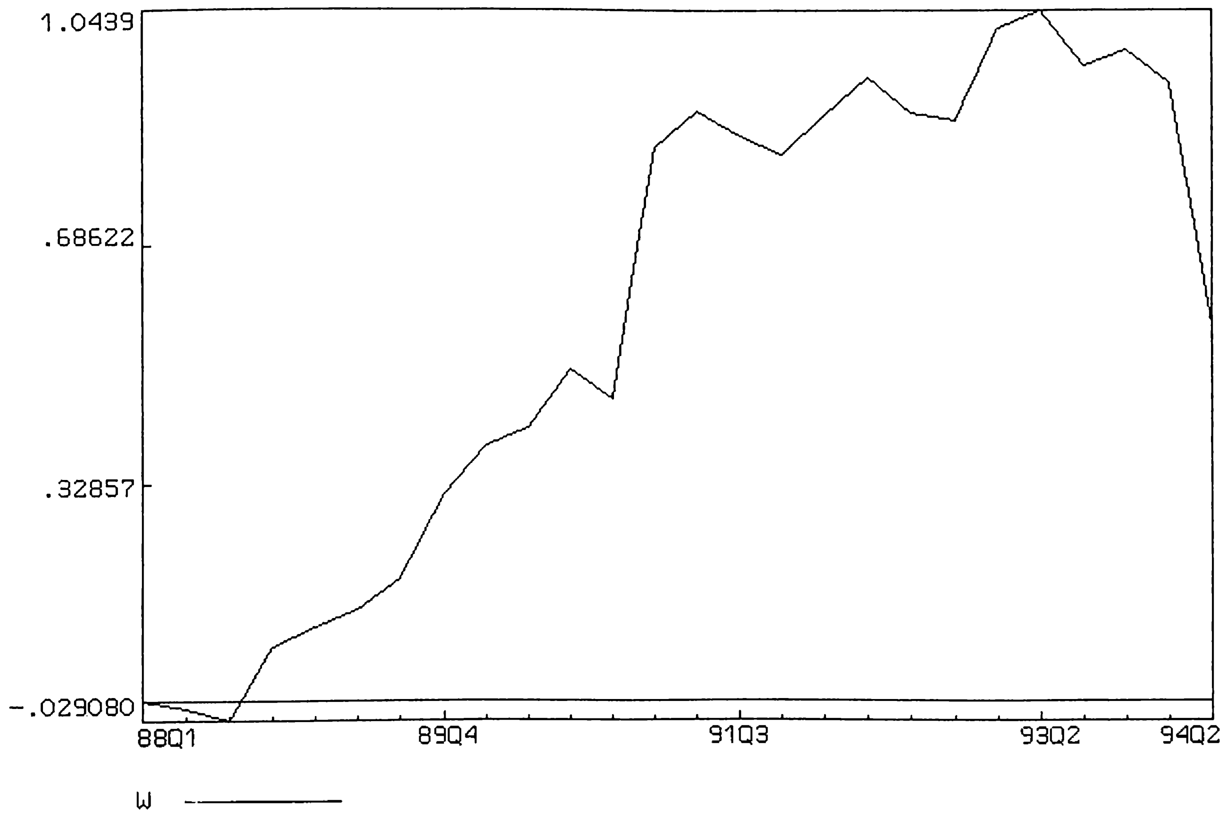
GRAPHIC 1

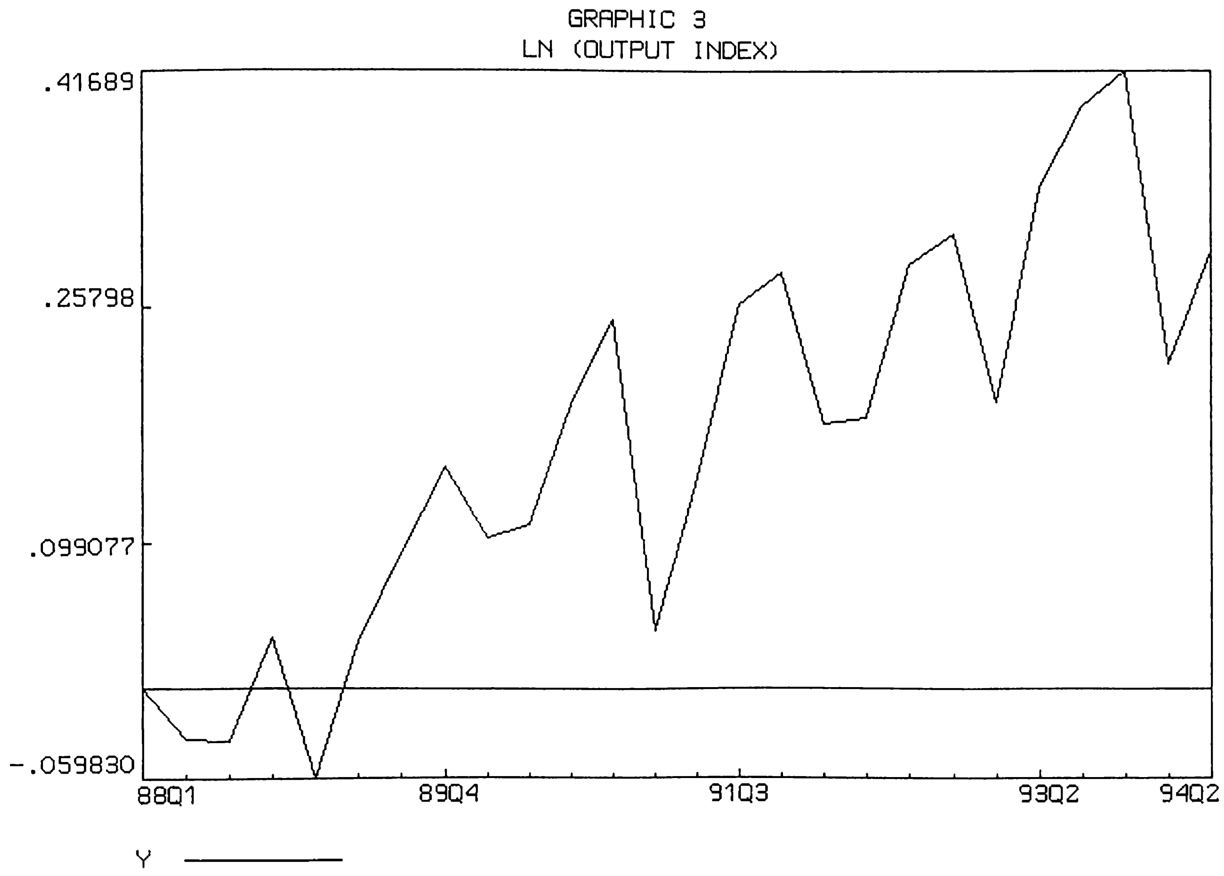
LN (EMPLOYMENT INDEX)



GRAPHIC 2

LN (REAL WAGE INDEX)



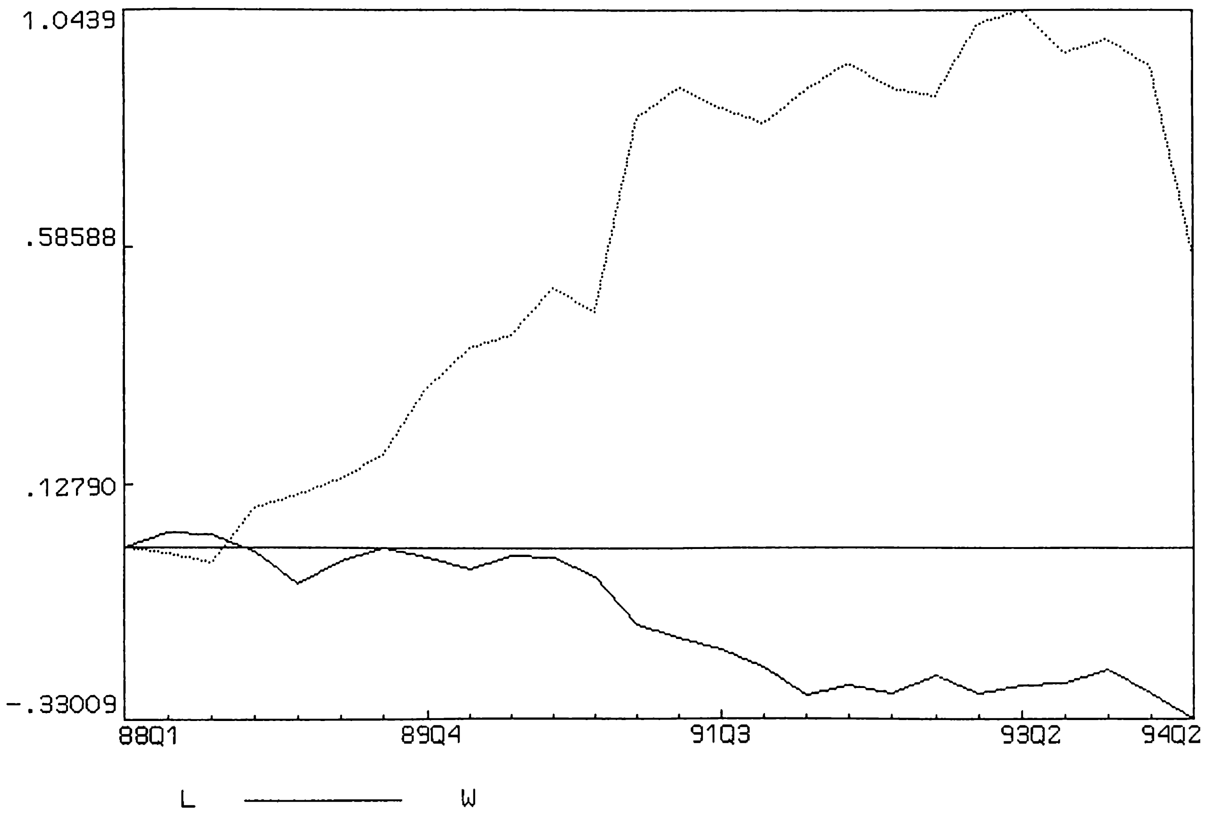


GRAPHIC 3
LN (OUTPUT INDEX)
.41689
.25798
.099077
-.059830
88Q1
89Q4
91Q3
93Q2
94Q2
Y


GRAPHIC 4
PLOT OF LN(EMPLOYMENT INDEX) VS. LN(OUTPUT INDEX)
.41689
.16790
-.081097
-.33009
88Q1
89Q4
91Q3
93Q2
94Q2
L
Y

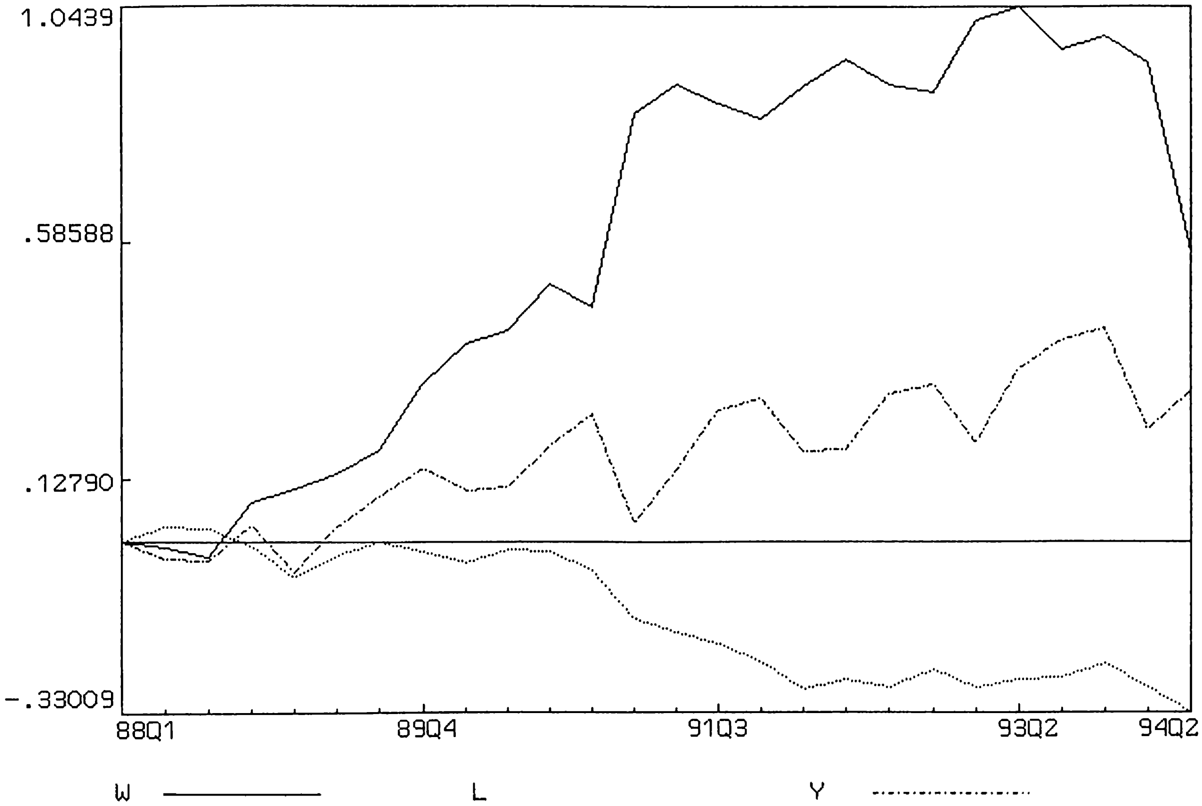
GRAPHIC 5

PLOT OF LN(REAL WAGE INDEX) VS. LN(EMPLOYMENT INDEX)

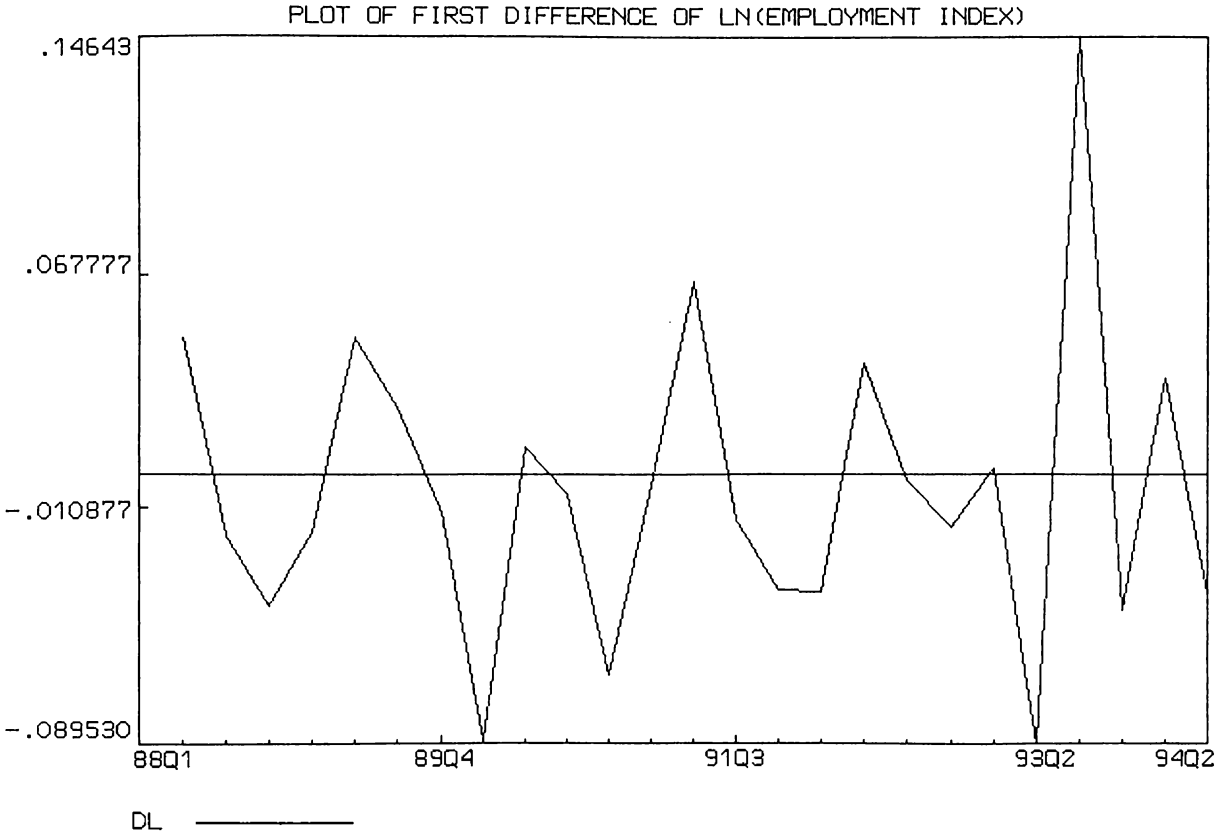


GRAPHIC 6

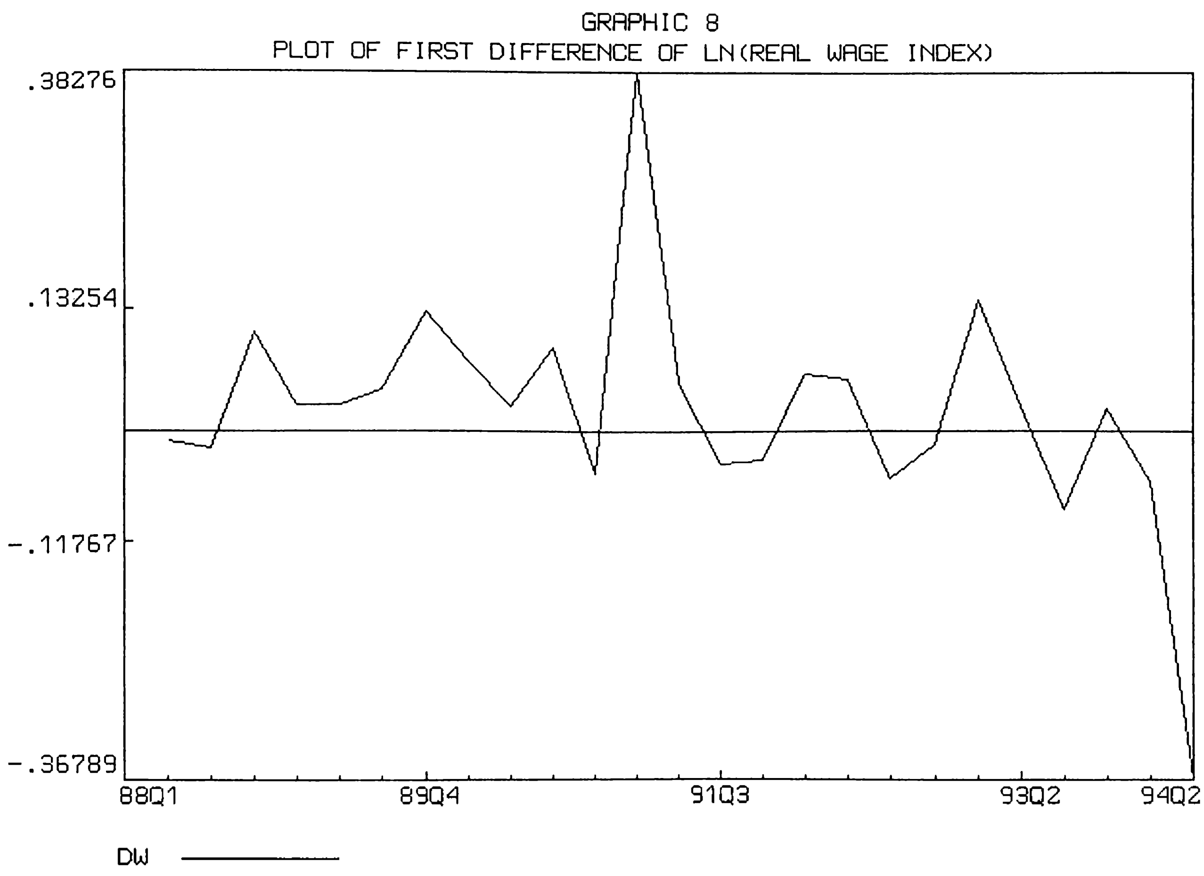
PLOT OF LN(EMPLOYMENT INDEX), LN(REAL WAGE INDEX) AND LN(OUTPUT INDEX)



GRAPHIC 7



PLOT OF FIRST DIFFERENCE OF LN(EMPLOYMENT INDEX)
.14643
.067777
-.010877
-.089530
88Q1
89Q4
91Q3
93Q2
94Q2
DL


GRAPHIC 8
PLOT OF FIRST DIFFERENCE OF LN(REAL WAGE INDEX)
.38276
.13254
-.11767
-.36789
88Q1
89Q4
91Q3
93Q2
94Q2
DW

GRAPHIC 9

PLOT OF FIRST DIFFERENCE OF LN(OUTPUT INDEX)