Staff Paper Series

Staff Paper P72-28 December 1972

THE MEASUREMENT OF BIASED TECHNICAL CHANGE IN THE MANY FACTORS CASE: U.S. AND JAPANESE AGRICULUTURE

By

Hans P. Binswanger

Department of Agricultural and Applied Economics

University of Minnesota
Institute of Agriculture
St. Paul, Minnesota 55108

Staff Paper P72-28 December 1972

The Measurement of Biased Technical Change in the Many Factors Case: U.S. and Japanese Agriculture

Hans P. Binswanger

Research Associate, Department of Agricultural and Applied Economics, University of Minnesota. Research for this paper was supported by the U.S. Agency of International Development first through a grant to the Department of Economics of the North Carolina State University and then by a grant to the University of Minnesota Economic Development Center. The conclusions do not necessarily reflect the position of the U.S.A.I.D.

Paper Presented at the Winter Meetings
of the Econometric Society
December 28-30, 1972
Toronto, Canada

THE MEASUREMENT OF BIASED TECHNICAL CHANGE IN THE MANY FACTORS CASE: U.S. AND JAPANESE AGRICULTURE

1. Introduction

This paper presents a way to measure factor saving biases of technical change, or more generally, of efficiency gains with more than two factors of production.* The methodology is then applied to the agricultural sectors of the U. S. (1912-1968) and Japan (1893-1962).

The purpose of measuring biases in two countries is to test the induced innovation hypothesis at a very basic level: If biases of technical change are exogenously given by fundamental laws of nature (physics, chemistry and biology), then we would expect that two countries, which both had strong factor efficiency growth in agriculture, would have experienced similar biases during the same time period. If, on the other hand, the state of the basic sciences does not restrict technological possibilities as strongly as to predetermine biases, economic variables such as factor prices, rate of interest, and extent of the market will have an influence on the biases, i.e. the biases will be endogenous. Therefore, we would expect them to differ in economies where substantial differences in the economic variables occurred over time.

In another paper (Binswanger 1972) I deal more thoroughly with the problem of induced innovation as it is discussed in the literature. That paper will also interpret the series of the biases presented here

---

*Sato (1970) derived a method to measure biases in the two factor case using CES and constant elasticity of derived demand production functions. He applied the method to the U. S. private nonfarm sector.

with respect to the induced innovation hypothesis. The general conclusion will be that biases are endogenously determined to a very large extent. Although the methodology used and the induced innovation hypothesis could apply to the economy as a whole, the agricultural sector was chosen because its product has undergone much less transformation than the output of other sectors of the economy, so that few measurement problems occur on the output side. Also a many-factor production process can provide more insight into the causes of the biases, and last but not least, agriculture provides a wealth of historic data which might be difficult to find in other industries.

The plan of this paper is as follows: First Hicks (1964) definition of biases is transformed to a definition in terms of factor shares which is more easily handled in the many-factor case than Hicks' definition. Then the theoretical model is derived. The following section deals with cross sectional estimation of cost function parameters which have to be known before biases can be estimated. The last section presents the derived series in graphical form with the numerical values included in the appendix.

2. Definitions of Hicks Neutrality and Biases

The definitions of biases have been derived to deal with technical change problems. Technical change is here defined as the development and adoption of new production techniques. Empirically it is, however, not possible to determine which part of total increase in factor productivity has been due to technical change alone (Nelson 1973). Part of the productivity gains have also been due to education, soil improvements, etc. At present it is not possible to measure biases of technical change alone, but only biases of total factor productivity. Part of these biases are due to education and other factor quality improvements. Therefore the term efficiency gains rather than technical change will be used.

Efficiency gains simply mean that the unit isoquant of a production process shifts closer to the origin. To characterize these shifts as to biases a particular point on the isoquant has to be considered. Farrell (1957) has introduced the following useful distinction between economic and technical efficiency (see figure 1).

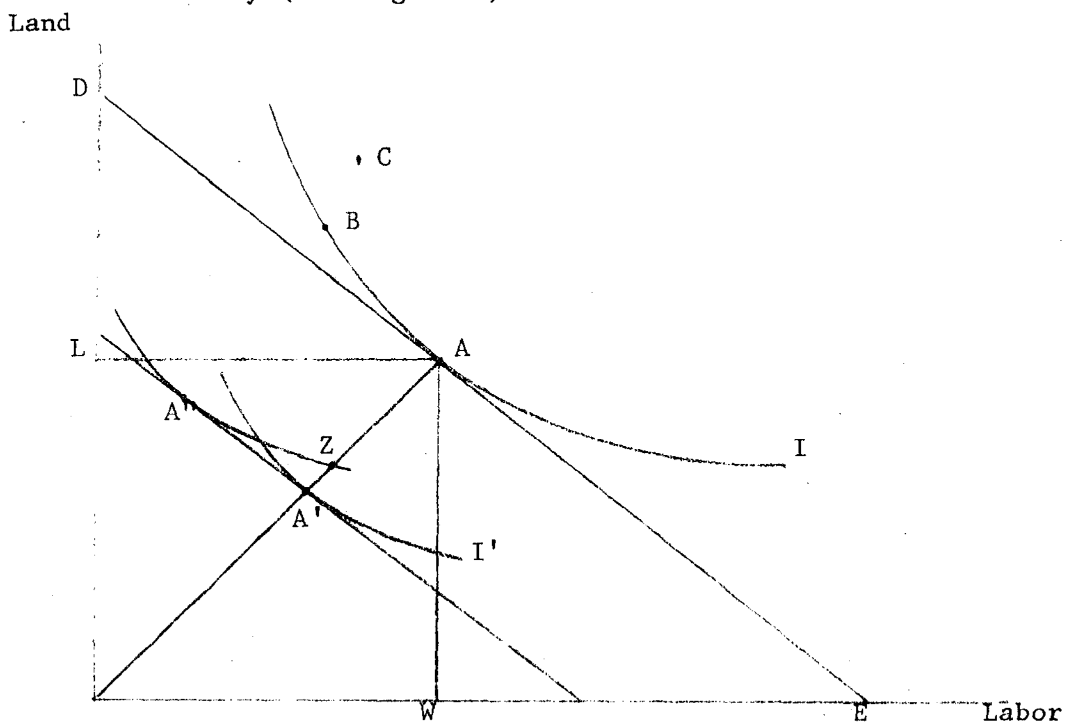

Figure 1. Technical and Economic Efficiency

Any point on the unit isoquant such as B or A is technically efficient, while C is not. For a given set of prices only one point is economically efficient; unit costs are only minimized at A. The theory of biased efficiency gains in the Hicksian sense asks how the economically efficient point moves inwards over time at constant factor price ratio. If it moves inwards along the ray OA to A' the efficiency gain is said to be Hicks neutral. If it moves to A'' the change has been labor saving. More specifically, efficiency gains are said to be labor saving, labor netural or labor using depending on whether, at constant factor prices, the labor-land ratio decreases, stays constant or increases. This definition can be immediately transformed into a definition in terms of factor shares at constant factor prices.

Efficiency gains are labor saving, labor neutral or labor using according to whether the labor share decreases, stays constant or increases at constant factor prices. This definition generalizes easily to the many factor case and will lead to one single measure of the biases for each factor. If a definition in terms of the factor ratios were used it would be necessary to consider n-1 factor ratios for each factor to determine biases. Therefore, the definition in terms of shares is used in the following chapters. The rate of the factor i bias is measured as:

$$B_i\big|_{\text{relative factor prices}} = \frac{d\alpha_i}{dt} \cdot \frac{1}{\alpha_i} \begin{matrix} < \\ = \\ > \end{matrix} 0 \rightarrow \text{Hicks} \begin{cases} \text{i-saving} \\ \text{i-neutral} \\ \text{i-using} \end{cases} \quad (1)$$

where α_i is the share of factor i in total costs.

To estimate biases it is, however, not possible to simply look at historic factor share changes. The observed share changes have come about through biased technical change and through ordinary factor substitution after changes in the prices of the factors. The basic problem is, therefore, to sort out to what extent the share changes have been due to biased technical change and to what extent to price changes. This can only be done, in a graphic sense, if the curvature of the isoquant is known. The substituion parameters of the production process have to be estimated before any biases can be measured. In the following sections this will be done for the agricultural sector using a cost function to characterize the production process.

3. Measurement of Biases with a Translog Cost Function

In my thesis (Binswanger 1973), I first derived a general theory to measure biases in the many-factor case for arbitrary twice differentialable production functions. For actual implementation a particular form of the production function has to be chosen. The production functions considered were, however, either too restrictive (Cobb-Douglas, CES, constant difference of elasticities of substitution) or complicated to use (generalized Leontief, Transcendental Logarithmic production function). In the case of the Transcendental Logarithmic (Translog) cost function (Christensen, Jorgensen, and Lau, 1970), the theory simplifies and estimation equations for its paramters are econometrically convenient. The theory is therefore derived directly in terms of this function.

Two models of measurement of biases are considered. Model A assumes variable rates of biases and is used to derive long term series of biases. Model B assumes the biases to occur at constant rates and can be used with regression methods. For the period when sufficient data are available both models will be used and their consistency will provide support for the model A estimate.

3.1 The Translog Case: Model A

Every production function has a minimum cost function as its dual. This function, which may not be expressible in closed form, even though the production function is, relates factor prices to the cost of the output. Therefore, the cost function contains all the information about the production process which the production function contains.

A minimum per unit cost function with technical change can be specialized into a factor augmention form.*

---

* See Solow (1967) for a discussion of factor augmentation. The production function in factor augmenting form is

$$Y = f[(X_1A_1), (X_2A_2), \ldots, (X_nA_n)]$$

(X_1A_1) is the effective quantity of factor X_1. An increase in A_1 has the same effect on output as an equiproportional increase in X_1 would have had prior to the increase in A_1. Therefore factor augmentation restricts technical change so that it cannot alter the form or the parameters of the production or cost function. It enters by changing the quantity of effective factor supply. It is immaterial whether effective factor supplies can be measureed or not, because producers will react to changes in marginal productivities of the factors and alter the factor inputs according to the unchanged parameters of the production or cost function. If the form of the function is known, one can test the factor augmenting hypothesis by testing for constancy of its coefficients over time. This test is presented in a later section.

$$U = f(W_1, W_2, \ldots, W_n, T) = \phi\left(\frac{W_1}{A_1}, \frac{W_2}{A_2}, \ldots, \frac{W_n}{A_n}\right) \qquad (2)$$

where U is per unit cost, W_i are the factor prices and T is a technical change variable or time. The A's are augmentation parameters corresponding to the ones of the dual production function. A proportional change in A_i has the inverse effect on the unit cost as a proportional change in the factor price i. As the MP of factor i is uniformly increased, more of it is substituted for others in exactly the same way as if instead the price of it had fallen.

Let $R_i = \frac{W_i}{A_i}$, the factor price of the augmented factor unit $(A_i X_i)$.

The Translog unit cost function can be written as

$$U = \nu_o \left(\prod_{i=1}^{n} R_i^{\nu_i} \right) \left(\prod_{i=1}^{n} R_i^{1/2 \sum_{j=1}^{n} \gamma_{ij} \ln R_j} \right) \qquad (3)$$

where ν_0, ν_i and γ_{ij} are the parameters of the function. The part within the first brackets is a Cobb Douglas function. If the cost function were Cobb Douglas then the production function would be also (for proof, see Hanoch, 1970). We therefore can think of the terms in the second bracket as amendments to the Cobb Douglas function which change the elasticities of substitution away from one (See equations 28 to 31 below). The functions allows arbitrary and variable elasticities of substitution among factors.

The function is linear logarithmes:

$$\ln U = \ln \nu_0 + \sum_i \nu_i \ln R_i + \frac{1}{2} \sum_i \sum_j \gamma_{ij} \ln R_i \ln R_j \ . \qquad (4)$$

The function can be considered a functional form in its own right or regarded as a logarithmic Taylor series expansion to the second term around input prices of 1 of an arbitrary twice differentiable cost function [Christensen, et al., 1970]. With the proper set of constraints on its parameters it can therefore be used as an approximation to any one of the known costs and production functions. As the simplest example, the constraints for Coub Douglas simply set all γ_{ij} to zero. The constraints for an approximation to the CES are more complicated [Christensen et al., 1970]. The following symmetry constraint holds for all Translog functions (equality of second cross derivatives)

$$\gamma_{ij} = \gamma_{ji} \qquad \text{for all } i, j, i \neq j \ . \qquad (5)$$

Also costs functions are homogeneous of degree one in prices. When all factor prices double unit costs will double. It can be shown that this implies:

$$\sum_i \gamma_i = 1$$

$$\sum_i \gamma_{ij} = 0, \qquad \sum_j \gamma_{ij} = 0 \ . \qquad (6)$$

To measure biases we need equations which explain factor shares in terms of factor prices. The Shepard Duality Theorem [Hanoch, 1970] gives one of the fundamental relationships between the cost and production function under cost minimization.

$$\frac{\partial U}{\partial W_i} = X_i . \tag{7}$$

In augmented units (7) becomes

$$\frac{\partial U}{\partial R_i} = \frac{\partial U}{\partial W_i}\frac{dW_i}{dR_i} = A_i X_i = Z_i . \tag{8}$$

where the Z_i are the factor quantities in the augmented unit space. The first derivatives of the Trnaslog function, with respect to the log of the factor prices, are equal to the shares:

$$\frac{\partial \ln U}{\partial \ln R_i} = \frac{\partial U}{\partial R_i} \cdot \frac{R_i}{U} = \frac{Z_i R_i}{U} = \frac{A_i X_i (W_i/A_i)}{U} = \frac{W_i X_i}{U} = \alpha_i \tag{9}$$

Taking these derivatives, we have:

$$\alpha_i = \nu_i + \sum_j \gamma_{ij} \ln R_j \qquad i = 1, \ldots, n. \tag{10}$$

Differentiating (10) totally we have

$$d\alpha_i = \sum_{j=1}^{n} \gamma_{ij}\, d \ln R_j \qquad i = 1, \ldots, n. \tag{11}$$

The proportional (log) change of a ratio is the difference of the proportional changes of its numerator and denominator.

$$d\alpha_i = \sum_{j=1}^{n} \gamma_{ij} (d \ln W_j - d \ln A_j) \qquad i = 1, \ldots, n. \tag{12}$$

Separating terms and using matrices

$$\begin{bmatrix} d\alpha_1 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ d\alpha_n \end{bmatrix} = \begin{bmatrix} \gamma_{11} & \cdots & \gamma_{1n} \\ \cdot & & \\ \cdot & & \\ \cdot & & \\ \cdot & & \\ \gamma_{n1} & \cdots & \gamma_{nn} \end{bmatrix} \begin{bmatrix} d \ln W_1 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ d \ln W_n \end{bmatrix} - \begin{bmatrix} \gamma_{11} & \cdots & \gamma_{1n} \\ \cdot & & \\ \cdot & & \\ \cdot & & \\ \cdot & & \\ \gamma_{n1} & & \gamma_{nn} \end{bmatrix} \begin{bmatrix} d \ln A_1 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ d \ln A_n \end{bmatrix} ,$$

or $d\alpha = \gamma d \ln W - \gamma d \ln A.$ (13)

γ is not of full rank due to the homogeneity constraint. But calling an arbitrary factor the n'th factor

$$\gamma_{in} = - \sum_{i=1}^{n-1} \gamma_{ij}. \tag{14}$$

Using (14) to remove γ_{in} from (13), we have

$$d\alpha_i = \sum_{j=1}^{n-1} \gamma_{ij}\, d\, w_j - \sum_{j=1}^{n-1} \gamma_{ij}\, d\, a_j, \tag{15}$$

where $dw_j = d\ln W_j - d\ln W_n = d\ln (\frac{W_j}{W_n})$

and $da_j = d\ln A_j - d\ln A_n = d\ln (\frac{A_j}{A_n})$.

Let Γ be the truncated (n-1) x (n-1) matrix of the γ_{ij} which is of full rank. Then

$$d\alpha_{(n-1)x1} = \Gamma\, dw - \Gamma\, da, \tag{16}$$

which gives us the solution for the changes in the A ratios:

$$da = dw - \Gamma^{-1}\, d\alpha. \tag{17}$$

With the discrete time equivalent of (17) time series of the augmentation series can be estimated, provided reliable estimates of the Γ^{-1} matrix are available. Going one step further, the share changes, which would have obtained, had factors prices remained constant can be estimated directly. They are the share changes needed to estimate the biases according to equation 1. Call these changes $d\alpha^*$, which can be obtained from system (16) by setting dw = 0. $d\alpha^*$ is the measure of share change which we need for (1). Then

$$d\alpha^* = -\Gamma da. \tag{18}$$

And substituting da from (17),

$$d\alpha^* = d\alpha - \Gamma \mathbf{dw}. \tag{19}$$

According to (19), we can immediately judge the nature of technical change for factors i-1, ..., n-1. Also, since

$$\sum_{i=1}^{n} d\alpha_i^* = 0,$$

we have also the solution for the n'th factor

$$d\alpha_n^* = -\sum_{i=1}^{n-1} d\alpha_i^*. \tag{20}$$

Equation (19) has a nice simplicity to it. To find out what the factor share changes would have been, had factor prices remained constant, simply subtract from the observed factor share changes that part which was caused by changing factor price ratios. The Γ matrix contains the information by how much the changes in factor price ratios alone could have altered shares. A completely heuristic derivation of (19) is also possible:

Writing (12) without technical change, i.e., with all dln A = 0, we have:

$$d\alpha_i = \sum_j \gamma_{ij}\ d\ \ln W_j \qquad i = 1, \ldots, n. \tag{21}$$

This is the share's change due to factor price changes alone. Now suppose that technical change over time alters the share by $d\alpha_i^*$, defined earlier as the change which would have occurred without factor price changes.

Then we could rewrite (21) for technical change

$$d\alpha_i = \sum_j \gamma_{ij}\ d\ \ln W_j + d\alpha_i^* \tag{22}$$

where $d\alpha_i$ is the observed change in shares and $d \ln W_j$ are the observed factor price changes. Converting to full rank as above, we then have

$$d\alpha = \Gamma \, dw + d\alpha^*$$

or

$$d\alpha^* = d\alpha - \Gamma \, dw, \tag{19}$$

which is the same as before. This derivation depends also on the factor-augmenting hypothesis because the Γ matrix must be constant.

Before (19) can be used with time series data the coefficients of the matrix have to be estimated. This must be done with cross section data where, ideally, all units are on exactly the same production function. We can then assume that all A_i are equal to one for all units and rewrite equation (10):

$$\alpha_i = \nu_i + \sum_j \gamma_{ij} \ln W_j + \varepsilon_i \qquad i = 1 \ldots, n \tag{23}$$

and use this system of equations to estimate the γ_{ij} coefficients. Of course one will never find a cross section where all units are on exactly the same production function. Ways to deal with this problem are discussed in the next section.

3.2 The Translog Case: Model B

Model A assumes that the rate of biases is not constant over time. This of course is the proper assumption if induced innovation is to be investigated over longer periods of time. For shorter time periods it is, however, possible to assume that the biases are constant. If this is done, biased technical change at constant exogenous rates can be introduced in the translog cost function in a similar way in which Christensen et.al., (1970) introduced it into the corresponding production function:

$$\ln U = \ln \nu_o + \sum_i \nu_i \ln W_i + \tfrac{1}{2} \sum_i \sum_j \gamma_{ij} \ln W_i \ln W_j + \nu_t \ln t + \omega_t (\ln t)^2 + \sum_i \omega_i \ln W_i \ln t \qquad (24)$$

where t stands for time.

Upon differentiation the share equations become:

$$\frac{\partial \ln U}{\partial \ln W_i} = \alpha_i = \nu_i + \sum_j \gamma_{ij} \ln W_j + \omega_i \ln t \qquad (25)$$

This is the estimation equation (23) with time entering as a variable. ω_i is the constant exogenous rate of factor i bias.

If (25) is used as a regression equation with a time series or a combination of cross section and time series, the introduction of time in this way will ensure that biased technical change at constant rates will not bias the estimates of the γ_{ij}. Furthermore the coefficients $\hat{\omega}_i$ can be used to derive another set of price corrected shares series, say $d\alpha_i^{**}$ which can be used with equation (1) to estimate the biases for the particular period:

$$d\alpha_i^{**} = \hat{\omega}_i \, d \ln t \qquad i = 1 \ldots, n. \qquad (26)$$

Of course this model cannot be used to extrapolate outside of the short regression period because then the assumption of a constant exogenous rate of bias is tenuous. However, the consistency of the $d\alpha_i^{**}$ series for the period in which both models can be used will be of great value to assess the quality of the series derived.

4. Cross-Sectional Estimation of the Parameters of the Cost Functions

The cross-sectional estimation of the cost function was done with state data from the United States. Japanese cross-section data were not gathered. If the factor-augmenting hypothesis holds, then the γ_{ij} parameters are the same for the United States and Japan and the U. S. γ_{ij} parameters also hold for Japan.*

Four sets of cross section data were obtained for 39 states or groups of states. The cross sections were derived from census and other agricultural statistics for the years 1949, 1954, 1959, and 1964. The combination of cross sections over time poses problems which are discussed in the section on error specification.

The time series component is important because it allows a test of the factor augmenting hypothesis (constancy of coefficients over time) and the estimation of biases by method B, by measuring the ω_i coefficients. Discussion of these two aspects is done towards the end of this chapter.

In general, Griliches' (1964) definitions of factors were used. He distinguishes the following five factors: land, labor, machinery, fertilizer and all others. Intermediate inputs are included in this list and the function fitted corresponds to a gross output function rather than a value added function.

---

*This does not imply that the countries are on the same production function. Differences in the A's are sufficient to place the unit isogenants of the two countries in entirely different positions in the positive orthant. Neither does it require the elasticities of substitution to be the same. They may differ according to equations (28) and (29) below.

Most of the data come from published USDA sources. Expenditures on factors usually are actual expenditures and, where applicable, inputed expenditures for wages of family members interest charges, depreciation and taxes. Quantity data are derived as price weighted indexes of physical units (land and fertilizer) or the sum of individually deflated expenditures (all other) or a combination of these methods (machinery and labor). The quantity data were already computed in Fishelson (1969), who used Griliches (1964) data with slight changes. Expenditure and quantity data are consistent with each other. The price data were obtained by dividing the expenditure data by the quantities.*

The estimation equations are as follows:

$$\alpha_{ik} = \nu_i + \sum_j \gamma_{ij} \ln W_{jk} + c_{ik}, \quad i = 1...n, \ k = 1...m. \qquad (27)$$

where k is the k'th observation unit. They are unaltered if neutral efficiency differences exist among states or time periods. Neutral differences would only alter the intercept ν_o of the cost function which drops out upon differentiation. If any left out factor such as education or research and extension affects efficiency neutrally, leaving them out of the estimation equation will not bias the results.

Nonneutral efficiency differences among the observational units will have the effect that the true α_i will differ for each observational unit; at equal factor prices shares will not be equal.** If such differences

*The amount of data transformations performed on this set of data and on the two sets of time series data discussed below and the diversity of sources precludes a thorough discussion here. A complete discussion of all data used can be found in Binswanger (1973)

**Nonneutral efficiency differences between 2 states implies that at equal factor prices, they will use factors in differing proportions. Factor shares will therefore differ even at equal factor prices occur among all units, the estimates of the coefficients of (27) will be biased. However, if such differences occur only among groups of states, the proper set of regional dummies will again lead to unbiased estimators. While the proper grouping might be questioned, dummies for five regions were therefore included in the regression equations. This should at least diminish the problem. Nonneutral differences might arise due to educational differences, differences in research and extension or differences in product mix.

If (27) is estimated with time series data, a time trend in the estimation equation will solve the problem of biases over time as explained in model B, provided the rates of biases stayed reasonably constant during the estimation period. Since the period was rather short (1949-1964), this assumption is not unreasonable.

Within each of the four cross sections, the error terms of the n-1 estimation equations are not independent, since for each state the same variables which might affect the shares in addition to the prices were left out of the model. If restrictions across equations ($\gamma_{ij} = \gamma_{ji}$) are imposed, OLS estimators are no longer efficient despite the fact that all equations contain the same explanatory variables on the right hand side (Theil 1971). Therefore, the seemingly unrelated regression problem applies and Restricted Generalized Least squares have to be applied to all equations simultaneously (Zellner 1962, 1963).*

*The Computer Program used was Triangle Universities Computing Center: Two and Three Stage Least Squares, Research Triangle Park, N.C., 1972 (TTLS).

If all four cross sections are pooled there is an additional problem of error interdependence over time. The correct way of handling both problems would be to specify an equation for each share in each year, then test and impose the symmetry and homogeneity constraints and the constraints that the γ_{ij} parameters are constant over time. This exceeded the capacity of the TTLS program. The correct procedure would also have required that one impose constraints of equality of the auto-correlation coefficients over time on the estimated variance covariance matrix which was not possible with TTLS.

The following procedure was therefore adopted: 1) Hypotheses not involving time concerning the γ_{ij} of the same or different shares equations were tested in models containing four shares equations using data from a single cross section only. These tests were also used to decide into which equation dummies should be included. 2) The testing of the constancy of the γ_{ij} parameters over time was done in models containing a separate equation for the same share in two cross sections. As an example, to test whether the γ_{ij} parameters of the labor share equation were constant over time a two equation GLS model containing a labor share equation for the 1949 data set and a labor share equation for the 1959 data set was estimated and a test performed whether the regression coefficients in the two equations were the same. 3) The actual estimation of the γ_{ij} coefficients was done with a data set which contained all four cross sections using a constrained GLS model containing four shares equations. This procedure took account of error interdependence among share equations but not of error interdependence over time. While the resulting estimates are unbiased, they will not be most efficient ones. No tests are performed with this regression and the t-ratios of the estimates are probably overstated.

The system to be estimated contains equations for five expenditure shares. But only four of these equations are linearly independent. So one equation has to be dropped. In a statistical sample the coefficients estimated will not be the same independent of which equation is dropped. Another question to be decided is in which equations to include regional dummies, i.e. for which factor to allow biased regional efficiency differences. Theoretical reasoning does not help much to make the above choices. Neither should the estimates of the coefficients be used as guides. Despite the fact that using tests of significance as criteria might lead to sequential estimation problems (Wallace and Ashar 1972), such tests were used. In the absence of theoretical justification they are the only information which is available. The specification was searched which would best satisfy the symmetry and homogenity constraints of the cost function; i.e. lead to the smallest relative increase in error sums of squares when imposed (smallest F-ratio). Since these constraints are beyond doubt, they can be used to eliminate certain specifications. It turned out that on average a model containing the equations for land, labor, machinery and fertilizer with regional dummies in all equations satisfied this criterion best. The homogeneity constraint was accepted in all four cross sections at the .05 level. The symmetry constraint was only rejected in the 1949 data set. The three other specifications tried performed less well. The Cobb-Douglas constraint ($\gamma_{ij} = 0$ for all i, j) was also tested and rejected in all specifications. Since the R^2 of the singl- equations was always in the range of .5 to .9, this could be expected. Only if the equation had no explanatory power at all could the constraints be accepted.

The test of constancy of the coefficients was done separately for each equation using the specification with regional dummies in all equations. A two-equation GLS model is fitted for each share with the 1949 data used for the first equation and the 1959 data for the second equation. The homogeneity constraint is imposed on the data, Table 1 shows the resulting F statistics.

Table 1. Results of test for constancy of coefficients over time

Equation	F-Statistic	dF	Critical F
Land	.36	4/60	
Labor	3.57	4/60	F .05 = 2.52
Machinery	3.14	4/60	F .01 = 3.65
Fertilizer	.69	4/60	

The hypothesis is never rejected at the .01 level of significance although it is rejected in two equations at the .05 level of significance. The tests can therefore be interpreted as weak support of the factor-augmenting hypothesis. Certainly the results would not suggest abandoning of the hypothesis for further work. The γ_{ij} estimates reported in Table 2 were arrived at by pooling the four cross sections and imposing the homogeneity and symmetry constraints (Table 2). The t-ratios are, therefore, probably overstated. They still appear to be quite low in some cases. However, $\gamma_{ij} = 0$ implies that

Table 2. Restricted estimates of the coefficients of the translog cost function and t-ratios[a]

Equation	Land	Labor	Machinery	Fertilizer	Ln year	Intercept	MN	GR	SE	GS[c]	Other[b]
	Variable										
Land	.07747 (6.02)	-.03613 (3.25)	.00478 (.47)	.01066 (2.14)	.00847 (1.47)	.2603 (9.96)	-.1021 (10.2)	-.0394 (4.1)	-.1073 (8.9)	-.0577 (4.7)	-.05678
Labor		-.06367 (3.67)	-.00661 (.59)	-.02805 (4.97)	-.05482 (9.08)	.5218 (14.91)	.0194 (1.63)	-.0016 (.15)	.0169 (1.09)	.0246 (1.63)	.13446
Machinery	(Symmetric)		-.03485 (1.31)	-.00877 (.97)	.02498 (4.66)	.0926 (3.46)	-.0033 (.41)	.0369 (5.08)	-.0186 (1.86)	.0072 (.73)	.04545
Fertilizer				.00068 (.12)	.00178 (.63)	.0745 (5.6)	.0104 (2.5)	-.0041 (1.10)	.0370 (7.24)	-.00247 (.49)	.02548
Other[b]											-.14861

[a]Critical values with 578 degrees of freedom are $t_{.05} = 1.96$ and $t_{.01} = 1.65$. T-ratios may be overstated due to error interdependence over time.

[b]Compiled using the homogeneity constraint, not estimated.

[c]MN, GR, SE, GS are dummies for mixed northern agriculture, grain farming states, Southeast, and Gulf states respectively. The intercept stands for Western States and the coefficients of MN, GR, SE, GS are deviations from this intercept.

the corresponding partial elasticity of substitution is one, since the following relationships between the γ_{ij} and the σ_{ij} and the η_{ij} (elasticities of factor demand) hold (for proof, see Binswanger 1973):*

$$\sigma_{ij} = \frac{1}{\alpha_i \alpha_j} \gamma_{ij} + 1 \qquad \text{for all } i \neq j \qquad (28)$$

$$\sigma_{ii} = \frac{1}{\alpha_i^2} (\gamma_{ii} + \alpha_i^2 - \alpha_i) \qquad (29)$$

$$\eta_{ij} = \frac{\gamma_{ij}}{\alpha_i} + \alpha_j \qquad \text{for all } i \neq j \qquad (30)$$

$$\eta_{ii} = \frac{\gamma_{ii}}{\alpha_i} + \alpha_i - 1, \qquad (31)$$

where α_i are the factor shares. Therefore, γ_{ij} close to zero with low t-ratio is not a "bad" result. The γ_{ij} parameters can be evaluated by looking at the implied elasticities of factor demand for the diagonal elements and the elasticities of substitution for the off-diagonal elements (Tables 3 and 4). They were computed according to equations (28, 29, 30, and 31), using the unweighted average factor shares of the 39 states in the period 1949-1964.

All own demand elasticities have the correct sign. The demand for land appears very inelastic. The demand elasticities for machinery and other inputs are larger than 1, a fact to keep in mind sin-e it implies that a rise in the corresponding prices will, other things equal, lead to a fall in the factor share. The lower part of Table 3 shows the values of the

---

*σ_{ij} is the partial elasticity of substitution as defined in Allen (1938, page 503). $\eta_{ij} = \frac{\partial X_i}{\partial W_j} \frac{W_j}{X_i}$ where W_j is the price of factor j and X_i the quantity of factor i.

demand elasticities if the function was Cobb-Douglas and the actual factor shares used were estimates of its coefficients.

Negative elasticities of substitution imply that the two factors are complements.*

The closest substitute of land is fertilizer, as one might expect. Machinery also appears to be a good substitute for land, while labor is not. Other inputs appear to combine with land in almost fixed proportions. Labor's best substitute seems to be other inputs, and not machinery, as initially expected. Considering that other inputs contain all intermediate inputs and outside services, the strong substitutability becomes more plausible, as intermediate inputs substitute for inputs produced with the use of labor on the farm itself. (Note that intermediate inputs produced and consumed on the same farm are neither included in input nor output statistics.) Also the substitutability between labor and machinery is still quite high.

Overall, the γ_{ij} estimates seem to be adequate. No absurd results were obtained. To see whether error interdependence over time had a large influence on the estimates, restricted estimates with the same model were also obtained for each of the four data sets separately. The estimates from the pooled data were compared with the average estimates for the four data sets individually. The estimates were very close. In particular both sets imply complementarity for the same factor pairs except the machinery-fertilizer pair. The own demand elasticities were very similar except that

---

*Own elasticities of substitution have little economic meaning. They are simply transforms of the factor demand elasticities, which explains why they cannot be infinitely large. They obey the following adding up constraint: $\sum_j \alpha_j \sigma_{ij} = 0$, (Allen 1938).

Table 3. Factor demand and cross demand elasticities[a] implied in the estimated γ_{ij} and the standard errors around their value in the Cobb-Douglas case[b]

	Land[d]	Labor	Machinery	Fertilizer	Other
Estimated Translog values[c]					
Land	-.3356 (.09)	.0613 (.07)	.1792 (.07)	.1062 (.03)	-.0112
Labor	.0308 (.04)	-.9109 (.06)	.1256 (.04)	-.0577 (.02)	.8122
Machinery	.1833 (.07)	.2560 (.08)	-1.0886 (.18)	-.0239 (.06)	.6733
Fertilizer	.4508 (.10)	-.4878 (.20)	-.0991 (.30)	-.9452 (.16)	1.0815
Other	-.0046	.6690	.2720	.1053	-1.0417
Cobb-Douglas values for comparison[e]					
Land	-.8491	.3008	.1475	.0356	.3652
Labor	.1509	-.6992	.1475	.0356	.3652
Fertilizer	.1509	.3008	-.8525	.0356	.3652
Machinery	.1509	.3008	.1475	-.9644	.3652
Other	.1509	.3008	.1475	.0356	-.6348

[a]Each element in the table is the elasticity of demand for the input in the row after a price change of the input in the column. These elasticities are not symmetric.

[b]The shares used are the same as for the Cobb-Douglas η_{ij}.

[c]$\eta_{ij} = \frac{\gamma_{ij}}{\alpha_i} + \alpha_j, \qquad \eta_{ii} = \frac{\gamma_{ii}}{\alpha_i} + \alpha_i - 1.$

[d]$SE(\eta_{ij}) = \frac{SE(\gamma_{ij})}{\alpha_i}.$

[e]$\eta_{ij} = \alpha_j, \quad \eta_{ii} = \alpha_i - 1.$

Table 4. Estimates of the partial elasticities of substitution and standard errors around 1[a]

	Land	Labor	Machinery	Fertilizer	Other
Land	-2.225	.204	1.215	2.987	-.031
Labor		-3.028	.851	-1.622	2.224
Machinery			-7.379	-.672	1.844
Fertilizer		Symmetric		-26.573	2.961
Other					-2.852

[a] $\sigma_{ij} = \frac{\gamma_{ij}}{\alpha_i \alpha_j} + 1, \quad \sigma_{ii} = \frac{1}{\alpha_i^2} (\gamma_{ii} + \alpha_i^2 - \alpha_i).$

The elasticities of substitution are symmetric.

other inputs had an elasticity of less than one for the average estimates of the four data sets. Some of the cross elasticities were not very stable over the four sets while the stability of the own elasticities was quite good.

5. The Empirical Measures of Biases in Efficiency Gains

This section presents the derived series of biases for the U.S. and Japan using model A. It also presents the series of actual factor shares. The data for the U. S. come from USDA published sources. The variables are constructed so that they correspond as closely as possible to the variables used in the cross section analysis. Total correspondence was, however, not, achievable.

The Japanese data came from Okawa, et al. (1965) with the exception of the interest rate series which was found in Ginko (1966). Variables construction was done to achieve close correspondence with the definitions used for the U. S. series. Of course, differences in method of data gathering and some definitional differences prevented exact correspondence. The details of the data are explained in Binswanger (1973).

The basic estimation equation for the biases are equations (19)

$$d\hat{\alpha}^* = d\alpha_i - \sum_{j=1}^{n-1} \hat{\gamma}_{ij}\ d\ \ln w_j \qquad (19)$$

where the α_i^* is the factor share i which would obtain in the absence of ordinary factor substitution due to price changes, $d\alpha_i$ is the actual total change in share i which includes the effect of the price changes. $d \ln w_i$ is the proportional change of the ratio of the price of factor i to the price of other inputs (a choice which is arbitrary). For actual estimation purposes series of three year moving averages of the shares and the factor prices were constructed. Then discrete differences of these moving averages at four year intervals were taken and used in the discrete change equivalent of (19). The $\hat{\gamma}_{ij}$ were the ones estimated in the U. S. cross-section regressions. It was assumed they were the same for the whole period and for Japan.

Equation (19) can be converted into a standardized measurement of the bias for each share by dividing the share changes through the levels of the actual shares in a base period. This leads to the discrete change equivalent of equation (1) which measures the rate of the biases.

$$B_i = \frac{\Delta\alpha_i^*}{\alpha_i^o} \lesseqgtr 0 \rightarrow \text{Hicks} \begin{cases} i \text{ saving} \\ i \text{ neutral} \\ i \text{ using} \end{cases} \qquad (1)$$

adding the B_i for all 4 year intervals (with B_i of the base period equal to 1) gives cumulative standardized series of α_i^* as a fraction of the base period.

An approach is only as good as its assumptions. The key assumptions here are simple cost minimization and the constancy of the γ_{ij} coefficients over time and space. The former assumption is no problem because it neither implies profit maximization nor nonintervention by the government in goods and factor markets. Only if the government regulates both prices and quantities of factors of production is there a big problem. Quantity controls alone will be reflected in corresponding price changes and vice versa and therefore will not disturb the measurements. They may of course have induced biases.

The constancy over time and space is more troublesome. When tested it was not supported as well as one might wish. But there is no way around the assumption.

Even the constancy over time assumption is not as restrictive as it sounds. It does not preclude variable elasticity of substitution and of factor demand. Furthermore these elasticities may have arbitrary values. The approach allows for neutral and nonneutral efficiency differences between the regions considered. In short it does not require countries to be on the same production function. Only the γ_{ij} parameters of the functions have to be the same.

The approach is also less restrictive than other approaches used up to now by allowing the production function to be nonhomogenous and allowing economies of scale, provided they affect all factors neutrally. It also uses five factors rather than 2, which means that it does not impose a separability constraint between capital and labor on the one hand the intermediate inputs on the other. From the point of view of its assumptions the approach should therefore be superior than other known approaches.

All resulting series are presented graphically. The corresponding numerical values are tabulated in the appendix. Figures 2 and 4 show cumulative bias series in percent of their 1912 and 1893 values in a semilogarithmic scale. The slope of each of the series is the B_i measure (equation 1) which measures the rate of the bias. The series themselves show cumulative effects. As an example, the fertilizer line in figure 2 indicates that, given the biases which occurred, the fertilizer share would have quadrupled between 1912 and 1962 had all the factor prices remained constant, i.e., had no factor substitution along a given production function occurred. The rather constant slope of the line indicates that the rate of the bias remained fairly constant throughout the period.

Figures 3 and 5 show the actual share movement for the US and Japan in the same semilogarithmic scale and as a percent of the 1912 value of the actual shares. The actual share changes reflect the influence of both bias and ordinary factor substitution.

According to figure 2 efficiency gains in the U. S. have been strongly fertilizer-using and machinery-using. At first they have been labor neutral and then substantially labor saving. Land has first been saved and then used

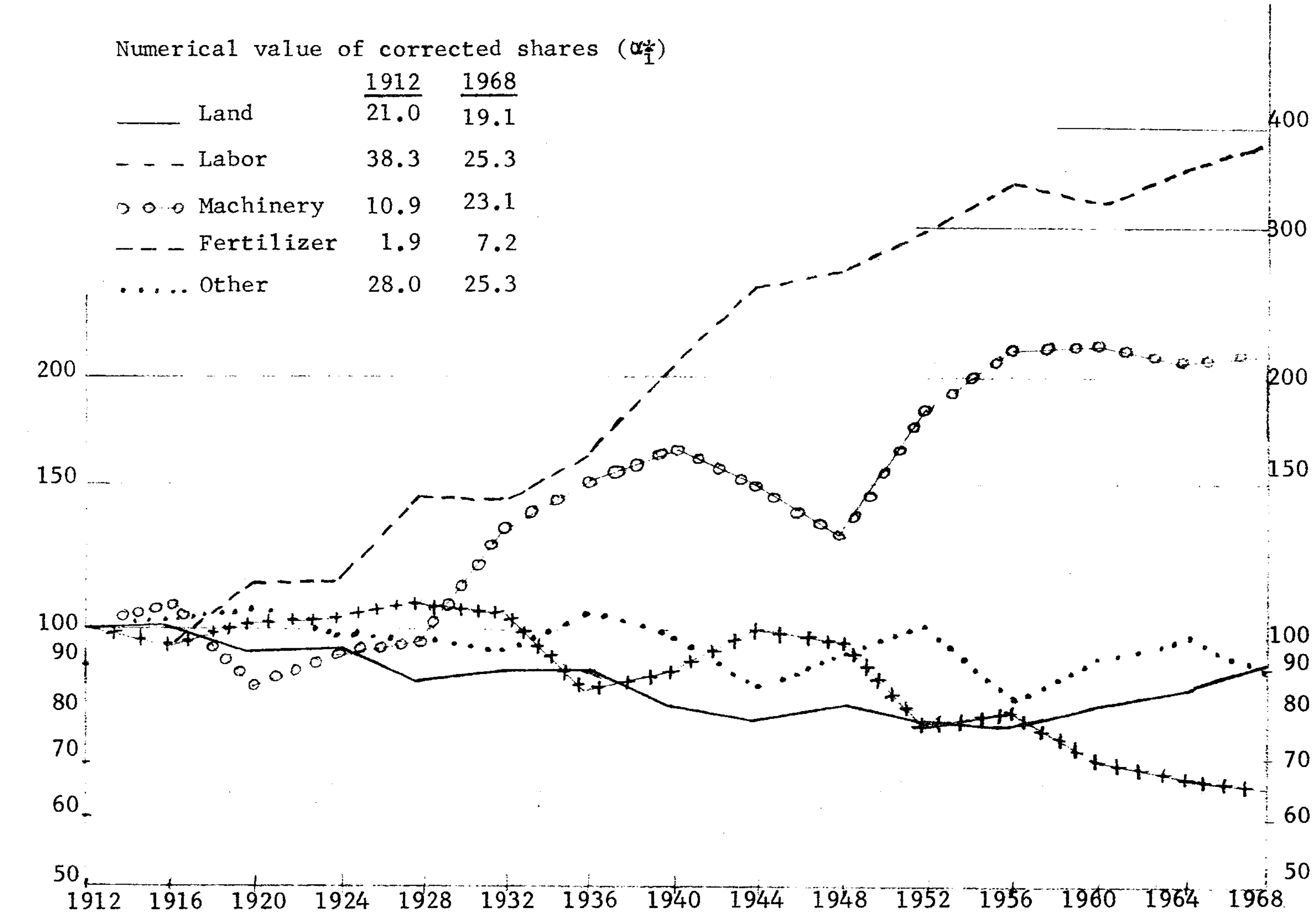

Figure 2. U. S. indices of biases in technical change: Model A estimates of $\alpha*$.
1912 = 100

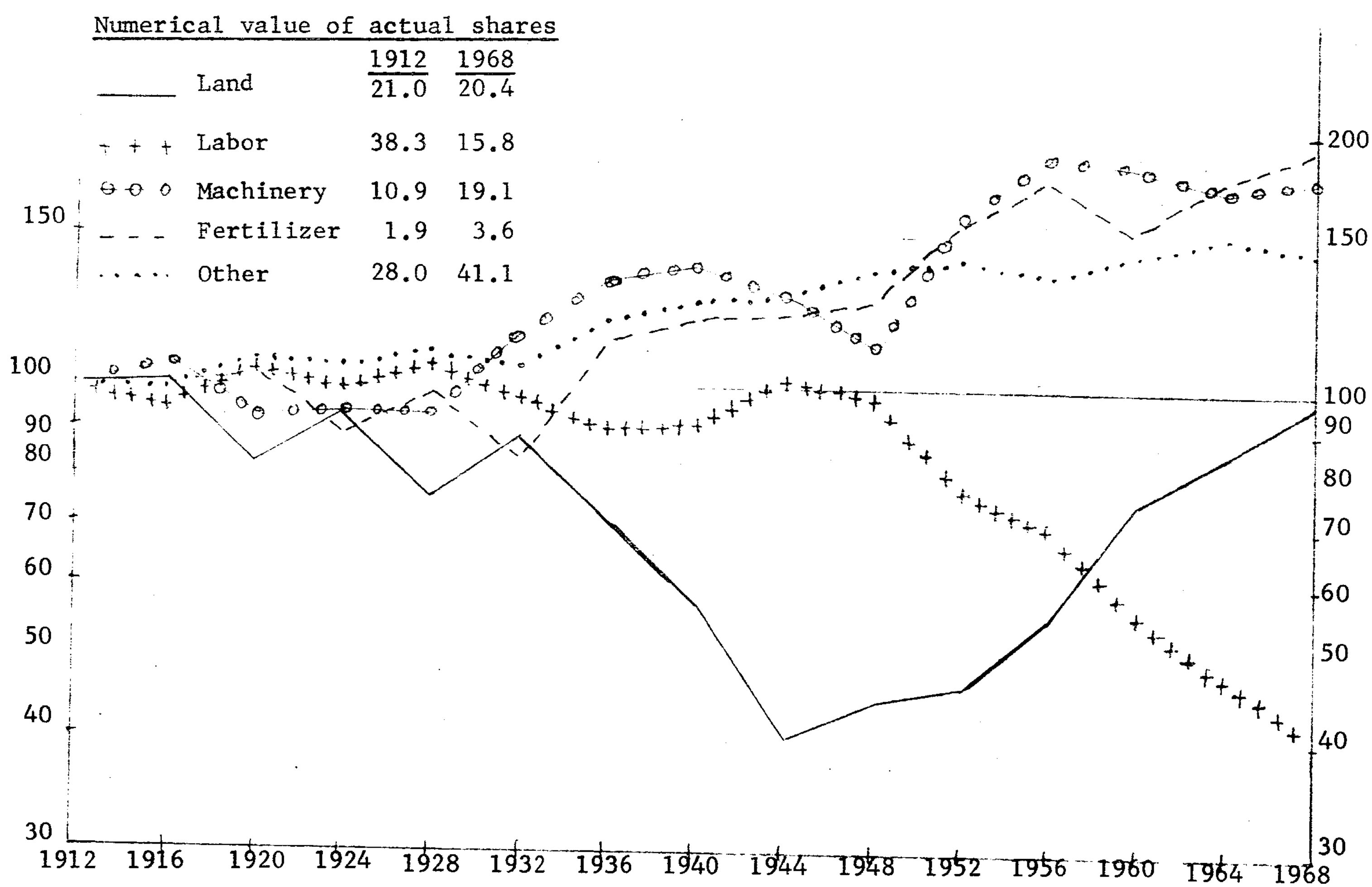

Figure 3. U. S. actural development of the factor shares, in percent of their 1912 value

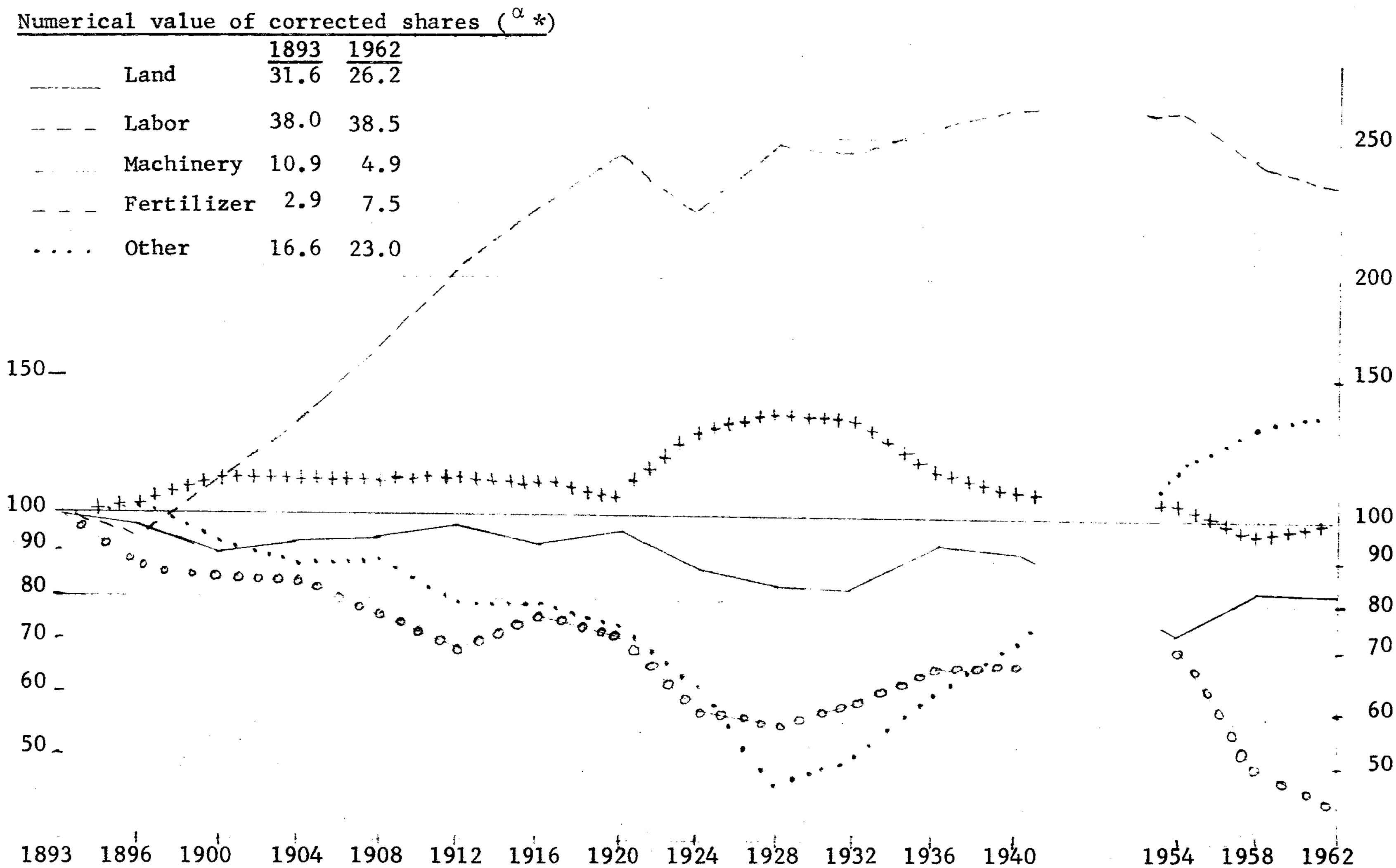

Figure 4. Japanese indices of biased technical change: Model A estimates of α^*.
1893 = 100

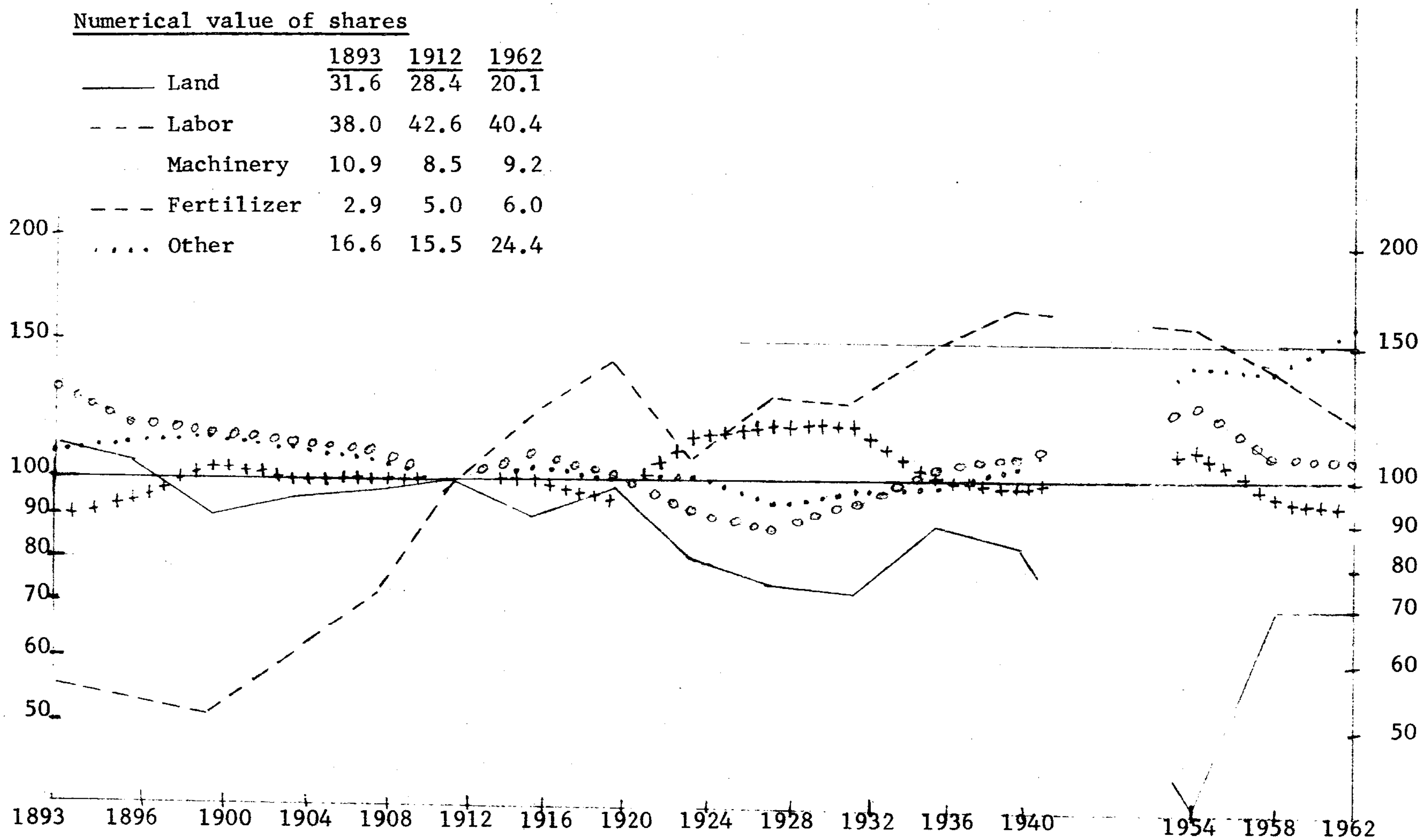

Figure 5. Japan: Actural development of the factor shares in percent of 1912 value.

while other inputs experienced neutral efficiency gains over the whole period.

Japanese efficiency gains have been fertilizer-using in a much earlier period than in the U. S.. After 1920 they were fertilizer neutral. Machinery had a negative overall bias, which is in strong contrast to the positive U. S. bias in machinery. Labor was used until 1928 and then saved while land had a slight overall negative bias. Other inputs have been saved until 1928 and then used.

Another conclusion which can be drawn is that biases are very important forces in the determination of factor shares. Of the 60% drop in the labor share in the U. S. between 1944 and 1968 the labor saving bias accounts for about 35% whereas the direct price influence accounts for the remaining 25% (neglecting any influence which the prices might have had in determining the biases themselves through induced innovation).

How much confidence can we have in the quality of the α^* series? This is a critical question before any interpretative work can be done.

If the estimates of the γ_{ij} were really far off, chances would be that over the long periods involved, which include two World Wars and the depression, some strange result would be immediately apparent in the α^* series. Such a result might be if one of the α^* series became negative. Smaller errors in the α_{ij}^* are of course not ruled out by such considerations. The errors could even be large enough to make inferences from small direction changes of the series impossible. That some such errors are present in the γ_{ij} became apparent when the matrix was inverted and estimates of the series of augmentation coefficients derived according to (25). These estimates showed the result that the augmentation coefficient of fertilizer becomes negative in both the Japanese and the U. S. case.

Does this result also invalidate the estimated α^* series? Not necessarily so for the following reasons: First, the properties of an estimator of the true elements of the γ^{-1} matrix, which inverts unbiased estimates of γ_{ij}, are unknown [Theil, 1971, p. 322]. Further, an error in just one of the γ_{ij} can lead to erroneous estimates of all the elements of the inverse. The largest elements of the inverse matrix corresponded to the smallest values of γ_{ij}, which also are the values with the smallest t-ratio (see Table 2) so that we have no assurance that they have the correct signs. The negative augmentation coefficient of fertilizer was therefore not judged important enough to also invalidate the α^* series.

The time coefficients ω_i estimated in the last chapter allow the estimation of biases using model B. The price corrected share changes $\Delta\alpha^{**}$ are computed for the period 1948-1964 for the U.S. as follows: $\Delta\alpha_i^{**} = \hat{\omega}_i$ dlnt under the assumption that the rate of the bias remained constant during that particular period or alternatively that $\hat{\omega}_i$ measures an average rate of bias. Apart from the fact that the $\hat{\gamma}_{ij}$ and the $\hat{\omega}_i$ were estimated in the same equations, the Model A estimates $\Delta\alpha_i^*$ have nothing to do with model B estimates $\Delta\alpha_i^{**}$ and therefore there is no reason, apart from chance, that they would come out to be the same if either set of estimates were wrong. Table 5 shows the comparison of the model B estimates with the model A estimates reported in the graphs.

Table 5. Comparison of Model A and Model B estimates of biases for the period 1948-1964 for the United States

Factor	1948 Level of Shares	Estimated share change due to technical change alone Model A 1948-1964 Δα*	 Model B 1948-1964 Δα**
Land	9.4%	+2.3%	+.7%
Labor	37.7%	-15.1%	-11.4%
Machinery	12.2%	+6.9%	+8.5%
Fertilizer	2.8%	+.5%	+1.6%

Both series estimate biases of the same sign and about of the same magnitude. That they would agree perfectly cannot be expected because of the differences in the underlying assumption. This comparison provides strong support of the α* series measured by model A.

It seems therefore that the derived series are of suggiciently high quality to make inferences about the indirect innovation hypothesis. The series, at least for fertilizer, labor, and machinery, diverge sufficiently to make the conclusion inevitable, that the biases are not exogenous to the economic system. If they were exogenous, both countries should have experienced similar biases. It is therefore worthwhile to continue research efforts in induced innovation. A forthcoming paper will deal with theoretical problems of this hypothesis, discuss other tests which have been done and present more interpretation of the derived series with respect to the hypothesis.

LIST OF REFERENCES

Allen, R. G. D. 1938. Mathematical analysis for economists. St. Martin's Press, Inc., New York.

Berndt, E. R. and L. R. Christensen. 1971. The translog production function and factor substitution in U. S. manufacturing, 1929-1968. Unpublished paper presented at the Winter meetings of the Econometric Society in New Orleans, Louisiana.

Binswanger, H. P. 1972. The induced innovation hypothesis reviewed in the light of some new evidence. Staff paper series #P.72-29, Department of Agricultural and Applied Economics, University of Minnesota, St. Paul, Minn.

Binswanger, H.P. 1973. The measurement of biased efficiency gains in U.S. and Japanese Argriculture to test the induced innovation hypothesis. Unpublished Ph.D. thesis. Department of Economics, North Carolina State University, Raleigh. University Microfilms, Ann Arbor, Michigan.

Diewert, W. E. 1971. An application of the Shephard duality theorem: A generalized Leontief production function. Journal of Political Economy, 70(3):481-505.

Farrell, M. J. 1957. The Measurement of Production Efficiency, Journal of the Royal Statistical Society, Series A, Vol. 120, Part III, p. 253-290.

Nadiri, M. I. 1970. Some approaches to the theory and measurement of total factor productivity. Journal of Economic Literature, 8(4).

Okawa, K. et al., eds. 1966. Estimates of long term economic statistics of Japan since 1868. Toyo Keizai Shinposha, Tokyo.

Sato, R. 1970. The estimation of biased technical progress. International Economic Review, 11(2):179-207.

Solow, R. M. 1967. Some recent developments in the theory of production. In Brown (ed.), The theory and empirical analysis of production. NBER, Studies in Income and Wealth, vol. 31.

Theil, H. 1971. Principles of econometrics. John Wiley & Sons, Inc., New York.

Timmer, C. P. 1970. On measuring technical efficiency. Food Research Institute Studies in Agricultural Economics, Trade and Development, 9(2).

Triangle Universities Computing Center. 1972. Program manual for two and three stage least squares. Research Triangle Park, North Carolina.

Uzawa, H. 1962. Production functions with constant elasticity of substitution. Review of Economic Studies, 30:291-299.

Wallace, T. D. and V. G. Ashar. 1972. Sequential methods in model construction. Review of Economics and Statistics, 54(2):172-178.

Zellner, A. 1962. An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. Journal of the American Statistical Association, 57:348-368.

Zellner, A. 1963. Estimators for seemingly unrelated regression equations: Some exact finite sample results. Journal of American Statistical Association, 58:977-992.

APPENDIX

Indices of biases, data on factor shares and data on prices used to derive the series of biases

Table 1. U.S. Factor shares adjusted for factor price influence: Indices of biases in technical change.

	Numerical values, as percent of total expenditures				
Year	Land	Labor	Mach.	Fert.	Other
1912	21.0	38.3	10.9	1.9	28.0
1916	21.2	36.7	11.6	1.8	28.7
1920	19.6	39.3	9.3	2.1	29.7
1924	20.0	39.7	10.3	2.2	27.8
1928	18.1	41.4	10.4	2.7	27.4
1932	18.8	40.3	14.3	2.7	24.0
1936	18.9	32.5	16.3	3.0	29.3
1940	16.8	34.3	17.6	3.9	27.5
1944	16.5	38.4	16.1	4.8	24.2
1948	17.1	37.2	13.9	5.1	26.7
1952	16.5	29.8	19.7	5.7	28.3
1956	16.3	30.6	23.1	6.5	23.4
1960	17.1	27.2	23.4	6.1	26.1
1964	17.8	25.8	22.4	6.7	27.3
1968	19.1	25.3	23.1	7.2	25.3

	Standardized, as percent of their 1910-1912 value				
1912	100	100	100	100	100
1916	101.1	95.8	106.8	96.5	102.6
1920	93.5	102.6	85.6	113.4	106.1
1924	95.4	103.7	94.8	113.9	99.4
1928	86.3	108.1	95.8	144.0	97.9
1932	89.7	105.2	131.7	142.4	85.4
1936	90.1	84.9	150.1	159.8	104.7
1940	80.1	89.6	162.1	204.1	98.3
1944	78.7	100.3	148.3	253.2	86.5
1948	81.5	97.2	128.0	267.9	95.4
1952	78.7	77.9	181.4	298.0	101.1
1956	77.7	79.9	212.7	341.8	83.6
1960	81.5	71.0	215.5	323.3	93.3
1964	84.9	67.4	206.3	354.4	97.6
1968	91.1	66.1	212.7	379.9	90.4

Table 2. Development of actual shares, U.S.

	Numerical values, as percent of total expenditures				
Year	Land	Labor	Mach.	Fert.	Other
1912	21.0	38.3	10.9	1.9	28.0
1916	21.6	36.5	11.6	1.9	28.4
1920	17.3	40.5	10.1	2.0	30.1
1924	19.7	38.5	10.3	1.7	29.7
1928	15.9	40.9	10.2	1.9	31.1
1932	18.6	37.6	12.6	1.6	29.7
1936	14.9	34.7	14.5	2.2	33.7
1940	12.0	35.3	15.1	2.3	35.2
1944	8.5	39.5	14.0	2.3	35.6
1948	9.4	37.7	12.2	2.4	38.3
1952	9.8	29.7	17.5	3.0	40.0
1956	11.5	27.4	20.1	3.3	37.8
1960	15.6	21.3	19.8	2.9	40.4
1964	17.5	18.3	18.5	3.3	42.3
1968	20.4	15.3	19.1	3.6	41.1

Table 3. U.S. input price/output price ratio indexes

Year	Land	Labor	Mach.	Fert.	Other
			1910-12 = 100		
1912	100	100	100	100	100
1916	113.3	106.8	110.0	105.7	103.8
1920	79.0	104.3	81.3	85.7	105.0
1924	119.0	134.5	111.7	93.1	106.6
1928	104.8	154.1	128.5	90.0	118.9
1932	160.8	194.7	231.5	128.6	101.5
1936	69.4	113.4	189.2	99.6	110.9
1940	87.3	179.0	288.8	103.4	160.1
1944	65.2	217.2	244.2	63.0	211.7
1948	73.0	247.8	226.6	50.4	222.8
1952	91.3	274.3	301.1	53.6	214.6
1956	145.8	407.9	423.7	65.9	229.6
1960	254.1	502.7	550.3	63.0	241.5
1964	338.1	610.0	651.2	63.2	270.9
1968	481.0	766.9	735.8	58.2	280.4

[a]For construction of the series and the data sources, see Binswanger 1973.

Table 4. Japanese factor shares adjusted for factor price influence: Indices of biases in technical change

Year	Numerical values, percent of total expenditures				
	Land	Labor	Mach.	Fert.	Other
1893	31.6	38.0	10.9	2.9	16.6
1896	31.2	39.4	9.4	2.8	17.3
1900	28.6	43.5	9.2	3.2	15.7
1904	29.6	43.0	9.1	3.8	14.5
1908	30.1	42.3	8.2	4.7	14.7
1912	30.8	42.9	7.4	5.8	13.0
1916	29.3	42.4	8.3	7.0	13.0
1920	30.6	41.1	7.8	8.2	12.3
1924	27.7	48.9	6.2	7.0	10.2
1928	26.4	51.4	6.1	8.4	7.7
1932	26.4	50.4	6.4	8.3	8.4
1936	29.2	43.1	7.1	8.8	11.8
1940	28.7	41.5	7.2	9.3	13.3
1954	23.1	40.3	7.8	9.3	19.5
1958	26.5	37.4	5.6	8.1	22.4
1962	26.2	38.5	4.9	7.5	23.0
	Standardized, as a percent of 1910-1912 value				
1893	102.6	88.6	147.3	50.0	127.7
1896	101.3	91.8	127.0	48.3	133.1
1900	92.9	101.4	124.3	55.2	121.0
1904	99.1	100.2	123.0	65.5	111.5
1908	97.7	98.6	110.8	81.0	113.1
1912	100.0	100.0	100.0	100.0	100.0
1916	95.1	98.8	112.1	120.7	100.0
1920	99.4	95.8	105.4	141.4	94.6
1924	89.9	114.0	83.8	120.7	78.4
1928	85.7	120.0	82.4	144.8	59.2
1932	85.7	117.5	86.5	143.1	64.6
1936	94.8	100.5	95.1	151.7	90.8
1940	93.2	96.7	97.2	160.3	102.3
1954	75.0	93.9	105.4	160.3	150.0
1958	86.0	87.1	75.7	139.7	172.3
1962	84.4	89.7	66.2	129.3	176.9

Table 5. Development of actual shares, Japan

Year	Land	Labor	Mach.	Fert.	Other
	Numerical values, percent of total expenditures				
1893	31.6	38.0	10.9	2.9	16.6
1896	30.1	40.0	9.9	2.7	17.2
1900	25.8	44.2	9.7	2.6	17.7
1904	27.5	43.0	9.5	3.1	16.9
1908	27.6	42.7	9.1	4.1	16.6
1912	28.4	42.6	8.5	5.0	15.5
1916	25.9	42.7	9.2	6.1	16.1
1920	28.0	40.6	8.7	7.1	15.5
1924	22.7	48.5	7.8	5.3	15.7
1928	21.4	50.1	7.5	6.4	14.6
1932	29.8	49.8	8.0	6.3	15.2
1936	25.2	43.2	8.8	7.4	15.3
1940	24.0	42.2	9.1	8.2	16.5
1954	11.6	44.7	10.8	7.9	22.0
1958	20.1	41.5	9.3	7.0	22.1
1962	20.1	40.4	9.2	6.0	24.4

[a]For construction of the series and the data sources, see Binswanger 1973.

Table 6. Japanese input price/output price ratio indexes

Year	Land	Labor	Mach.	Fert.	Other
		1910-12 = 100			
1893	120.6	80.5	143.6	190.8	113.0
1896	112.9	85.4	129.4	165.2	115.9
1900	94.4	94.9	124.0	148.7	112.9
1904	99.0	93.7	120.5	127.9	104.8
1908	97.6	94.6	110.2	118.2	106.1
1912	100.0	100.0	100.0	100.0	100.0
1916	97.7	111.0	113.7	116.1	113.4
1920	99.2	105.0	102.8	93.8	99.2
1924	92.7	141.1	96.3	74.6	107.7
1928	93.8	153.7	93.6	71.9	104.2
1932	100.3	172.5	105.1	73.7	118.7
1936	96.4	122.4	88.8	62.6	101.1
1940	87.4	117.1	84.4	79.1	105.6
1954	44.0	113.0	82.5	38.2	122.7
1958	97.2	138.1	78.6	32.9	126.0
1962	109.1	170.5	60.9	27.6	116.3

a For construction of the series and the data sources see Binswanger 1973.