equations in time series are prone to produce r's very near unity because during the regression period (e.g. post-war) all the series tend to have the same time trend, such high correlations being usually regarded as of doubtful significance from the forecasting viewpoint. Two practices are common to avoid the difficulty -
(i) Introduce time $t$ as an indvar;
(ii) Operate the regression on the deltas of the data $\left(\Delta x_{t}=x_{t}-x_{t-1}\right)$
As to (i), the coefficients of the indvars (except $t$ ) are those which would be found if trend $t$ were eliminated from all other variables. In what follows we deal only with (ii). It will suffice to confine attention to the simple (i.e. two-variable) case.

Let the model be

$$
\begin{equation*}
Y_{t}=\alpha+\beta X_{t}+u_{t}, t=1,2, \ldots, T, \tag{1}
\end{equation*}
$$

where the error term $u_{t}$ is regular (i.e. for all $t E u_{t}=0$, $E u^{2}{ }_{t}=\sigma^{2}, E u_{t^{\prime}} u_{t^{\prime}}\left(t^{\prime} \neq t\right)=0$ ). Then, if $b$ be the regression estimate of $\beta$,

$$
\begin{equation*}
b=\beta+\mathbb{E} x_{t} u_{t} / \Sigma x_{t}^{2} \tag{2}
\end{equation*}
$$

so that $\mathrm{E} \mathrm{b}=\beta$ with variance

$$
\begin{equation*}
\operatorname{var} b=E(b-\beta)^{2}=\sigma^{2} / \Sigma x_{t}^{2} \tag{3}
\end{equation*}
$$

classical results, of course. The $\Delta$ version of (1) is

$$
\begin{equation*}
Y_{t}^{\prime}=\beta X_{t}^{\prime}+u_{t^{\prime}}^{\prime} t=2,3, \ldots, T, \tag{4}
\end{equation*}
$$

where $Y_{t}^{\prime}=Y_{t}=Y_{t}-Y_{t-1}$, etc. There are now (T-1) terms. The error term $u_{t}^{\prime}$ is, however, no longer regular since obviously


If (1) and (4) (with an additional relation from (1), say $Y_{1}=\alpha+\beta X_{1}+u_{1}$, to make T relations in all) are both solved by maximum likelihood ( $1 / 2 \pm$ ) the estimates from a given realization of $\alpha$ and $\beta$ will be identical. In fact, if the probability element of the vector $u$ is

$$
\begin{equation*}
f\left(u_{1}, u_{2}, \ldots, u_{T T}\right) \quad \Pi d u_{t} \tag{5}
\end{equation*}
$$

the ML solution is found as the values of the parameters (e. g. $\alpha, \beta$ ) which maximize $f$, regarding the $u_{t}$ in $f$ as functions of the parameters and the data (e. g. as given by (1). If in (5) we make the linear transformation (in matrix form)

$$
\begin{equation*}
u^{i}=A u \tag{6}
\end{equation*}
$$

where $A$ is any non-singular square matrix with numerical elements, (5) transforms into

$$
\begin{equation*}
\left|A^{-1}\right| g\left(u_{1}^{t}, u_{2}^{i}, \ldots, u_{T}^{i}\right) \Pi d u_{t}{ }^{\prime} \tag{7}
\end{equation*}
$$

where $g$ is the function $f$ after the transformation. Since in (7) the positive determinant $|A|^{-1}$ is a constant (i. e. independent of the parameters), the problem of the maximization of $f$ and gare identical and the maximizing values of the parameters the same. In our particular application the matrix $A$ is
(8)A $\equiv\left|\begin{array}{cccccc}1 & 0 & 0 & \ldots & 0 & 0 \\ -1 & 1 & 0 & \ldots & 0 & 0 \\ 0 & -1 & 1 & \ldots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \ldots & -1 & 1\end{array}\right|$

## LS Regression Applied to Delta Version (4)

Invariably, however, when the regression problem is deltaized the assumption is made that the error term $u^{\prime}$ is regular, which assumption amounts to a wrong specification if the basic model is (1). Usually a constant term is added, which would indeed be formally consistent with the model:-

$$
\begin{equation*}
Y_{t}=\alpha+\beta X_{t}+\gamma t+u_{t} \tag{9}
\end{equation*}
$$

i.e. as a t (i) in the opening paragraph.

When (4) is regarded as a problem in least squares the estimate $b^{\prime}$ of $\beta$ is

$$
\begin{equation*}
b^{2}=\beta+\Sigma\left(x_{t}-x_{t-1}\right)\left(u_{t}-u_{t-1}\right) / \Sigma\left(x_{t}-x_{t-1}\right)^{2} \tag{10}
\end{equation*}
$$

so that $b^{i}$ is still an unbiased estimate of $\beta$.

Its variance,
$\operatorname{var} b^{\prime}=2 \sigma^{2}\left(\sum_{1}^{T}{x^{8}}^{2}{ }_{t}-\sum_{i}^{T} x_{t}^{\prime} x_{t-1}^{\prime}\right) /\left(\sum_{1}^{T} x^{\prime}{ }^{2}{ }_{t}\right),{ }^{2}$
recalling that $X_{t}^{i}=X_{t}-X_{t-1}=x_{t}-x_{t-1}$ and that now the $\Sigma^{i} s$ on the right have ( $T-1$ ) or ( $T-2$ ) terms.

We cannot compare the efficiency of $b$ and $b$ 'for all values of $T$ using the variance formulae (3) and (11) in general algebraic terms so we must have recourse to particular cases.

## Case 1

Let $X_{t}=t(t=1,2, \ldots, T)$, the very common equalspaced indvar case. Then

$$
\begin{equation*}
\Sigma x_{t}^{2}=T\left(T^{2}-1\right) / 12 \tag{12}
\end{equation*}
$$

and, from (3)

$$
\begin{equation*}
\operatorname{var} b=12 \sigma^{2} / T\left(T^{2}-1\right) \tag{13}
\end{equation*}
$$

All the $x_{t}^{\prime}$ are unity, so that, from (11),

$$
\begin{equation*}
\operatorname{var} b^{3}-2 \sigma^{2} /(T-1)^{2} \tag{14}
\end{equation*}
$$

so that if the efficiency $\mathbb{D}$ of $b^{\prime}$ in relation to $b=\operatorname{var} b / \operatorname{var} b^{\prime}$,

$$
\begin{equation*}
E=6(T-1) / T(T+1) \tag{15}
\end{equation*}
$$

The methods are equally efficient $(\mathbb{T}=1)$ for $T=2,3$. Thereafter the efficiency of $\mathrm{b}^{\prime}$ diminishes rapidly, in fact approximately as $6 / T$.

## Case 2

Often we notice a tendency for the indvar to cluster near the median so that our second constructed example will illustrate this.

Let there be 2 T observations so that $\mathrm{X}_{\mathrm{t}}(\mathrm{t}=1,2, \ldots, 2 \mathrm{~T})$ is

$$
-T^{2},-(T-1),{ }^{2} \ldots,-2^{2},-I^{2}, 1^{2}, 2^{2}, \ldots(T-1)^{2}, T^{2}
$$

Using the sum $S_{4}$ of the fourth powers of the natural numbers
$1,2, \ldots, T$, namely

$$
\begin{equation*}
S_{4}=\frac{T}{30}(T+1)(2 T+1)\left(3 T^{2}+3 T-1\right), \tag{16}
\end{equation*}
$$

we find, from (3)

$$
\begin{equation*}
\operatorname{var} \mathrm{b}=15 \sigma^{2} / \mathrm{T}(\mathrm{~T}+1)(2 \mathrm{~T}+1)\left(3 \mathrm{~T}^{2}+3 \mathrm{~T}-1\right) \tag{17}
\end{equation*}
$$

having noted that $\overline{\mathrm{X}}=0$ so that $\mathrm{X}_{\mathrm{t}}=\mathrm{x}_{\mathrm{t}}$.
As regards var $b^{\prime}$, the sequence $x^{\prime}{ }_{t}$ is -

$$
2 T-1,2 T-3, \ldots, 5,3,2,3,5, \ldots, 2 T-3,2 T-1,
$$

(2T - 1) terms in all, so that, after some elementary algebra, and using (11) -

$$
\begin{equation*}
\operatorname{var} b^{\prime}=18 \sigma^{2}\left(4 \mathrm{~T}^{2}-6\right) /\left(8 \mathrm{~T}^{3}-2 \mathrm{~T}+6\right)^{2} \tag{18}
\end{equation*}
$$

and efficiency E of estimate $\mathrm{b}^{\prime}$ is

$$
\begin{equation*}
E=5\left(8 T^{3}-2 T+6\right)^{2} / 6 T(T+1)(2 T+1)\left(3 T^{2}+3 T-1\right)\left(4 T^{2}-6\right), \tag{19}
\end{equation*}
$$

tending to $5 / 18 \mathrm{~T}$, when T is large. We recall, however, that for this Case 2, number of observations is not $T$, but $2 T=T$, say, whence limiting value of $\operatorname{dis} 5 / 9 \mathrm{~T}^{\prime}$, in comparison with $6 / \mathrm{T}^{\prime}$ for Case 1 . In the more typical Case 2 the efficiency of the delta procedure estimate b' (in relation to b) is even worse than in Case 1. Both are very bad.

## A Remark

The variances of $b$ given by (13) and (17) are not $O\left(\mathrm{~T}^{-1}\right)$ as in classical theory. In fact, in the foregoing exposé no regard wes psid to orders of magnitude. This would have been achieved by multiplying all the indvar velues as given by $\mathrm{KT}^{-1}$ in Case 1 and by $\mathrm{KT}^{-2}$ in Case 2, where K is independent of T. This treatment would render both estimates of var $\mathrm{b}^{\text {i }}$ of order $0\left(T^{0}\right)$. Using LS with the deltas the estimates $b^{\prime}$ are no longer consistent, as not tending to $\beta$ as $T$ tends to infinity. The values of $\mathbb{E}$ (15) and (19) would not be affected.

The General Case
The relative efficiency $E$ is $0\left(\mathrm{~T}^{-1}\right)$. If
the indvar $X_{t}$ can be represented by a polynomial of degree $r$ in $t, \sum X_{t}$ is $O\left(T^{r+1)}\right.$. Using this formula with var $b$ and var $b^{\prime}$ given by (3) and (i1) we find var $b=0\left(T^{-2 T-1}\right.$ ) and (since $\Delta X_{t}=X_{t}^{\prime}$ is $O\left(T^{t-1}\right)$ var $b^{\prime}=O\left(T^{-2 T}\right)$ always $E=O\left(T^{-1}\right)$ as in Cases 1 and 2.

## Consequence of Assumption of $u^{\prime}$ Regular

Suppose, on the contrary, that in (4) $u^{\prime}$, by the DW or $r$ tests, can be regarded as regular, variance $\sigma^{2}$, what are the implications for $Y_{t}$ ? Clearly -

$$
\begin{equation*}
Y_{t}=\alpha+\beta X_{t}+u_{t} \tag{20}
\end{equation*}
$$

but $u_{t}$ can no longer be regarded as regular, since it is heteroskedastic. In fact -

$$
\begin{equation*}
u_{t}=\sum_{t^{\prime}=1}^{t} u_{t^{\prime}} \tag{21}
\end{equation*}
$$

so that var $u_{t}=t \sigma^{2}$. Such a bizarre situation would be outside all experience. Let us, nevertheless follow it through, wrongly assuming that $\beta$ can be estimated by $\mathrm{b}^{\prime \prime}$, using LS regression. Then

$$
\begin{equation*}
b^{\prime \prime}=\Sigma Y_{t}\left(X_{t}-\bar{X}\right) / \Sigma\left(X_{t}-\bar{X}^{2}\right)^{2} \tag{2,2}
\end{equation*}
$$

which, on substitution from (20), becomes

$$
\begin{equation*}
\mathbf{b}^{\prime \prime}=\beta+\Sigma \mathrm{u}_{\mathrm{t}} \mathrm{x}_{\mathrm{t}} / \Sigma \mathrm{x}^{2} \mathrm{t}^{\prime} \tag{23}
\end{equation*}
$$

so that $\mathrm{Eb}^{\prime \prime}=\beta$. However -
which seems to be an ordinary magnitude, i. e. $O\left(T^{0}\right)$ : we have little intexest in estoblishing this firmly. If this is true then $b^{\prime \prime}$ does not tend towerds $\beta$ even when $T$ tends towards infinity. It is worthless as en estimete.

Jven if we satisfy ourselves es to the homoskedecity and non-autoregression of residuals in $\Delta X_{t}$ and $\Delta Y_{t}$ regression, i. e. that $u_{t}$ is regular, we should reelise the oddity of these assumptions for the relationship between the originel deta $X_{t}$ and $Y_{t}$. At present decision whether to use the original data or their deltas seems lergely a matter of whim or instinct, which is not good enough. Both cannot be right and criteria should be used in making a choice.

An Example

With $X_{t}$ gross national expenditure at $Y_{t}$ money (ennual everage) 1949-1965 ( $T=17$ ) the regression coefficient $b$ for $Y_{t}$ on $X_{t}$ is 0.2640 with ESE (estimated standard error) $0.00552, T=.997$, while for the deltes $b^{i}=0.189 . \quad$ with $E S E=$ $0.0730, r=.81$ (15d.f., $P \leqslant .001$ ). The efficiency of $b^{\prime}$ as an estimate of the theoretical $\beta$ is only . 0057. b is incomparably better than $b^{\prime}$ as an estimate of $\beta$.

On the other hend if one's objective is the estimation of $\Delta Y_{t}$ from $\Delta X_{t}$ (perhaps for forecasting) it is better to use the regression with $b^{\prime}$ then that from $Y_{t}$ on $X_{t}$, deriving the calculated $\Delta Y_{t c}$ ex post from the $Y_{t c}$. The values of the criterion of
goodness-of-fit $\Sigma\left(\Delta Y_{t}-\Delta Y_{t c}\right)^{2}$ are 345 and 448, so that the delta regression, despite its inferior estimate of b' yields a substantially better calculated value of $\mathbb{\mathbb { Y } _ { t }}$.

But the efficient estimation of the increments $\Delta Y_{t}$ is in conflict with the efficient estimation of $Y_{t}$ : We mean that
t
${ }_{t^{\prime}}^{\Sigma}=I^{\Delta Y_{t^{\prime}} c^{\prime}}$
where the $\Delta Y_{\text {tic }}$ have to be estimated by delta regression is less efficient as an estimate of $Y_{\text {tc }}$ than is the value calculated from the direct $Y_{t}$ on $\Sigma_{t}$ regression by the residual sum squares $\Sigma\left(Y_{t}-Y_{t c}\right)^{2}$ test. This is obvious since the direct $Y_{t}$ regression by definition minimizes this expression.

Conclusion
Wstimation of coefficients by LS regression from delta regression is highly inefficient. The hypothesis of residual regularity in the delta form of model is bizarre for its implication with regard to the error term of relation between absolute values. If, however this regularity can be regarded as tenable the delta regression can be used efficiently only for estimating the increments $\Delta Y_{t}$ and not the $Y_{t}$ themselves.

There is no reason why these conclusions, based on simple regression, should not apply to multivariate regression or to models of several equations.

Our professional consciences may be uneasy about those very high correlations in the original deta. It is certainly consoling to find a satisfactory correlation between the deltas of the data since thereby we can be reasonably sure that the original high correlation was not due solely to the fact that each was closely related to time trend $t$. This is a role for the deltas.

Better still to regress on $X_{t}$ and $t$ together and to find a significent coefficient for $X_{t}$. If $t$ is also significant (and the residual nonautoregressed) we have a reasonable forecasting equation.

A point to assuage our tortured consciences. If the ind.vars we know are all strongly correlated with time trend $t$, it is plausible to assume that those we don't know have the same property. The indvar t may act, in a certain measure act as a proxy for these, instead of requiring the error term to carry all the brunt. Time trend $t$ may be a more respectable indvar than we customarily think. If $t$ has a significant coefficient residual error variance will be reduced by its inclusion. Too large residual errors are the main bugbear of forecasting formulae.

