This PDF is a selection from an out-of-print volume from the National Bureau of Economic Research

Volume Title: Annals of Economic and Social Measurement, Volume 2, number 4

Volume Author/Editor: Sanford V. Berg, editor
Volume Publisher:
Volume URL: http://www.nber.org/books/aesm73-4

Publication Date: October 1973

Chapter Title: A Test for Systematic Variation in Regression Coefficients
Chapter Author: David A. Belsley
Chapter URL: http://www.nber.org/chapters/c9940
Chapter pages in book: (p. 492-500)

## A TEST FOR SYSTEMATIC VARIATION IN REGRESSION COEFFICIENTS

> by David A. Belsley*

This paper offers a statistical test of the constancy of the parameters of a inear regression. The $F$ test is basea on transformed residuals which resull from OLS applied to the giten equation ander the mull hypothesis of constancy.

## Some Notation

We consider the model

$$
\begin{align*}
& y(t)=x^{\prime}(t) \beta(t)+u(t)  \tag{1}\\
& \beta(t)=\Gamma_{z}(t)+u(t)
\end{align*}
$$

where
$x(t), z(t) K$ and $R$ vectors, respectively,
$\varepsilon(t)$ spherically distributed with $E x \varepsilon^{\prime}=\sigma^{2} I$,
$u(t)$ independent over time with Eut $=\sigma_{u}^{2} \Omega$.
(See preceding article for motivation.
In what follows we consider the special case $\sigma_{u}^{2}=0$. i.e., variation in $\beta(t)$ is systematic and non random. Hence, we may write

$$
\begin{align*}
y(t) & =x^{\prime}(t) \Gamma z(t)+\varepsilon(t) \quad \Gamma=\left[\ddot{i}_{1} \ldots \ddot{\prime}_{\mathrm{R}}\right]  \tag{2}\\
& =\left[x^{\prime}(t) \otimes z^{\prime}(t)\right] \Lambda+\varepsilon(t)
\end{align*}
$$

where

$$
\Lambda=\left[\begin{array}{c}
\ddots 1 \\
\vdots \\
\vdots \\
i_{R}
\end{array}\right] .
$$

Let

$$
\begin{array}{rrr}
Y=[y(t)], & X=\left[\begin{array}{c}
x^{\prime}(1) \\
\vdots \\
x^{\prime}(T)
\end{array}\right], & Z=\left[\begin{array}{c}
z^{\prime}(1) \\
\vdots \\
z^{\prime}(T)
\end{array}\right] \quad D=\left[\begin{array}{c}
x^{\prime}(1) \otimes z^{\prime}(1) \\
\vdots \\
\vdots \\
x^{\prime}(T) \otimes z^{\prime}(T)
\end{array}\right] . \\
& T \times K & T \times R
\end{array}
$$

Then (2) becomes

$$
\begin{equation*}
Y=D \Lambda+\varepsilon \tag{3}
\end{equation*}
$$

* Research supported by National Science Foundation Grant GJ-1154x to the National Bureau of Economic Research, Inc. Research Report W0006. This report has rot undergone the full criticai review accorded the National Bureau's studies, including review by the Board of Directors.
and we note that we may write

$$
\begin{equation*}
D-\left[y_{1} y_{2} \ldots z_{R j}[X Q 1]\right. \tag{4}
\end{equation*}
$$

where $y_{r}=$ diag $Z_{r}$ and $Z_{r}$ is the $r$ th column of $Z$.
Thus, (3) becomes

$$
\begin{equation*}
Y=\sum_{r=1}^{N} y_{r} x_{i_{r}}+\varepsilon \tag{5}
\end{equation*}
$$

## Remarks

Our purpose here is to determine a test of the null hypothesis that $\beta(\beta)=\beta$, i.e., is constant. for all $t$. Clearly a regression could be run on (3) direetly if the $z^{\circ}$ s were known, but alternative modeling tests, would be cumbersome given the size of ( $D D)^{-1}$ even for moderate $K$ and $R$.

In what follows a two-step test is determined that looks to be efficient and does not require inversion ol $D^{\prime} D$. Alternative $Z$ matrices may be compared with a mini. mum of computation. The first step is OLS of $Y$ on $X$ without regard to $Z$. The second step consists ol regressing a translormed set of residuals from step one on the similaty transformed $z^{\circ}$. $H_{0}$ maty be tested with the results of the second regression.

## STEP ONE: OLS $Y$ ON $\lambda$

First regress ) on 1 to get
(6)

$$
\begin{aligned}
b & =\left(X^{\prime} X\right)^{1} X^{\prime} \gamma \\
& =\left(X^{\prime} X\right)^{1} X^{\prime} D \Lambda+\left(X^{\prime} X\right)^{-1} X^{\prime \prime}: \\
& =\left(X^{\prime} X\right)^{-1} X^{\prime} \sum_{r} \psi_{r} X_{i r}+\left(X^{\prime} X\right)^{-1} X^{\prime \prime}:
\end{aligned}
$$

and

$$
\begin{aligned}
\ddots & \equiv Y-X h=H\} \quad\left(H=I-X\left(X^{\prime} X\right)^{-1} X^{\prime}\right) \\
& =H(D \Lambda+a] \\
& =\left[H \not y_{1} I \ldots M y_{R} X\right] \Lambda+H: \\
& \equiv\left[I_{1} \ldots I_{R}\right] \Lambda+H: \\
& =\sum_{r=1}^{N} V_{r i r}+H_{i}
\end{aligned}
$$

where the $V_{r}$ are the residual matrices from an anxiliary regression of $z_{r}, I$ on $I$.

This regression need not be run in pratetice. The relevanee of $b_{r}$ is seen from

$$
H \not X_{r} X_{r}=\not \mathscr{Z}_{r} X-X\left(X^{\prime} X\right)^{\prime} X^{\prime} z_{r} X=Z_{r} A-X B_{r} \equiv \mathfrak{I}_{r}
$$

where $B_{r}$ is the set of regression coefficients from $\mathcal{Z}_{r} X=X B_{r}+V_{r}{ }^{\prime}$
Thus we have

$$
\begin{equation*}
\ell^{\prime}=\Sigma \mathbf{V}_{r i r}^{\prime}+H z \tag{8}
\end{equation*}
$$

We recall that $H$ is idempotent. has rank $T-K$, and hence there exists an orthogonal $C$ such that $C^{\prime} H C=\left[\begin{array}{cc}I_{r-k} & 0 \\ 0 & 0\end{array}\right] \equiv G$. Further we note $H V_{r}=V_{r}$. $r=1 \ldots R$ and $H^{e}=c$. Hence, we may write
(9)

$$
\begin{aligned}
C^{\prime} H C C^{\prime} e & =C^{\prime} H C C^{\prime} \Sigma V_{r i r}+C^{\prime} H C C^{\prime}: \\
G C^{\prime} e^{\prime} & =G C^{\prime} \Sigma V_{r i r}+G C^{\prime \prime}
\end{aligned}
$$

OT
and. partitioning $C=\left[C_{1} C_{2}\right]$ so that the first $T-K$ rows of $(9)$ become

$$
\begin{align*}
f \equiv C_{1}^{\prime} e & =C_{1} \sum_{r=1}^{R} V_{r i r}^{\prime}+C_{1}^{\prime} \varepsilon  \tag{10}\\
& =C_{1}^{\prime} \sum_{r=2}^{R} \psi_{r} X_{i r}+\eta r^{2}
\end{align*}
$$

This last inequality comes from noting that $V_{r}=H \neq X$. and hence $C V_{r}=$ $C^{\prime} H \not{ }^{2}, X=C^{\prime} H C C^{\prime} \not X_{r} X=G C^{\prime} \not y_{r} X$, which mplies $C_{1}^{\prime} 1_{r}=C_{1}^{\prime}, X$. We have also let $C_{1} k \equiv \eta$.

We also note that $\eta$ is spherically distributed, since $E \eta=0 . \mathrm{V} \eta=E \eta \eta^{\prime}=$ $E C_{1}^{\prime} \varepsilon c^{\prime} C_{1}=\sigma_{\varepsilon}^{2} C_{1}^{\prime} C_{1}=\sigma_{\varepsilon}^{2} I_{T-K}$. due to the orthogonality of $C^{C}$.

It is the transformed residuals $f=C_{1}^{\prime}$ e that we make use of in step two. The transformation $C_{i}^{\prime}$ comes from finding an orthogonai set of eigenvectors of $H=I-X\left(X^{\prime} X\right)^{-1} X^{\prime}$, and hence $f$ depends only on knowledge of $X$ and $Y$ and does not require knowledge of $Z$.

## Step Two

It is clear from (10) that the residuals from step one depend in a very involved way on the interrelation of $X$ and $Z$ through the terns $y_{,} X$. However. under the nuli hypothesis $H_{0}: \beta(t)=\beta$, these terms disappear, and a simpier test is available.

Consider a mechanical regression of $f$ on $Z$ transformed by $C_{1}^{\prime}$ ( which depends only on $X$ ):

$$
\begin{equation*}
f=C_{1} Z \delta+\psi \tag{11}
\end{equation*}
$$

; In passing we note from (6) that

$$
\begin{aligned}
b & =\Sigma\left(X^{\prime} X^{\prime}\right)_{r} x_{r}+1 . S^{\prime} X^{:} X^{\prime} \\
& =\Sigma B_{r}+\left(X^{\prime}\right)^{-1} X^{\prime} \because
\end{aligned}
$$

Hence, $E h=\Sigma B_{r i r}$, a weighted sum of the $F_{r}$. and $V(b)=\sigma^{2}(X)^{-1}$
: This latter sum goes from $r=2$ to $R$ since, if $Z_{1}$, the first cal. of $Z$ is a column sector of all ones. then $Y_{1}=I$ and henee $V_{1} \equiv y_{1} X-X B_{1}=X-X B_{1}$, the least squares residuals of the aumiliary equation $X=X B_{1}+V_{1}$. These residuals must necessatrily be zero, since $B_{1}=I$ does the trick of minimizing the sum of squares. Hence, $C_{1} V_{1}=0=C_{1} X_{1} X=C_{1}, X$.

OLS gives
(12)

$$
\begin{aligned}
d & =\left(Z C_{1} C_{1} Z\right)^{-1} Z C_{1} f \quad \text { and from }(10) \\
& =\left(Z C_{1} C_{1}^{\prime} Z\right)^{-1} Z C_{1} C_{1} \Sigma y_{r} x_{i r}+\left(Z C_{1} C_{1} Z\right)^{\prime} Z C_{1} C_{1}: \\
& =(Z Q Z)^{-1} Z Q \sum_{r=2}^{R} y_{r} X_{i r}+(Z Q Z)^{1} Z Q
\end{aligned}
$$

where $Q \equiv C_{1} C_{1}$.
Under the null hypothesis $H_{0}: \beta(t)=\beta$, ir $=0$ for $r=2 \ldots R$, and hence the first term of ( 12 ) is 0 . That is, under $H_{n}$ :

$$
\begin{align*}
d & =(Z Q Z)^{-1} Z Q!  \tag{13}\\
& =(Z Q Z)^{-1} Z C_{1} f
\end{align*}
$$

In addition, from (10) we have under $H_{0}$ that
(14)

$$
f=C_{1} c
$$

Further, we note for future reference that $Q$ is idempotent since $Q Q=$ $C_{1} C_{1}^{\prime} C_{1} C^{\prime}=C_{1} I C_{1}=C_{1} C_{1}^{\prime}=Q$ and of rank $T-K$

Now consider the residuals $g$ of this second step; using (13) and (14).
(15)

$$
\begin{aligned}
g & \equiv f-C_{1} Z d \\
& =C_{1} \varepsilon-C_{1} Z(Z Q Z)^{-1} Z Q \varepsilon \\
& =C_{1}\left[I-Z(Z Q Z)^{-1} Z Q\right] \varepsilon \\
& \equiv N \varepsilon \quad \text { where we iet } N=C_{1}\left[I-Z(Z Q Z)^{-1} Z^{\prime} Q\right] .
\end{aligned}
$$

Now
(16)

$$
\begin{aligned}
g g & =\varepsilon N N \varepsilon \\
& =\varepsilon\left[I-Q Z(Z Q Z)^{-1} Z\right] C_{1} C_{1}\left[I-Z(Z Q Z)^{-1} Z Q\right] \varepsilon \\
& =\varepsilon\left[Q-Q Z(Z Q Z)^{-1} Z Q\right]\left[Q-Q Z(Z Q Z)^{-1} Z Q\right] \varepsilon \\
& \equiv \varepsilon M M \varepsilon \quad \text { where } M \equiv Q-Q Z(Z Q Z)^{-1} Z Q \\
& \equiv \varepsilon M:
\end{aligned}
$$

since $M$ is seen to be idempotent with $\rho(M)=\operatorname{tr} M=T-K-R$. And hence,
(17)

$$
g^{\prime} g \leftrightarrow \sigma_{\varepsilon}^{2} X_{T}^{2} \cdot \kappa-R
$$

From (13) we have

$$
\begin{gather*}
\mathrm{d}=(Z Q Z)^{-1} Z Q \varepsilon \equiv B r  \tag{18}\\
498
\end{gather*}
$$

and

$$
\begin{aligned}
B M & =\left(Z^{\prime} Q Z\right)^{-1} Z Q\left[Q-Q Z(Z Q Z)^{1} Z^{\prime} Q\right] \\
& =\left(Z^{\prime} Q Z\right)^{-1} Z^{\prime} Q-(Z Q Z)^{1} Z Q=0 .
\end{aligned}
$$

Hence, the linear form (18) is distributed independently of the quadratic form (17) and the usual tests of significance on $d$ may take place. Under $H_{0}: E d=0$, and hence a $t$ value for a specific $d$ at $T-K-R$ degrees of freedom in excess of the test level rejects the null hypothesis.

Boston Collegre, and

National Bureau of Economic Researdh

## KALMAN FILTER MODELS

## A BAYESIAN APPROACH TO ESTIMATION OF TIME-VARYING REGRESSION COEFFICIENTS

by Alfanander H. Sarris*

The origins of time-rarying linear regression coefficients are discussed, and it is noted that tim:' toriation cannot be estimeted unless some resirictions arc placed on the infinite forms of possible time changes For cxample, a Markor structure imposed a priori on the coefficiont renders them cstimable. The struclure impose's an incomplelely specificd prior prob ability distribution on the cocfficiens. The prior become's completely determined throngh fitting it to the date. Botys theorem is then used to deriee an cstimator of the parameters. Ender the assumption of perfece prior fit. the Bayes cstimator is unbiased, minimum ratiance. cond orthogonal to the residuals. Under the assumption of incomplete prior fit. the optimatity propertice of the extmator hold asymptoticalis: Finally. the problem of identifing the best Markot structure that fas the parametcrs is examined, and a Bavesian solution is proposed. This last discussion indicates the limitutions of any method that attempts to identity time-rarying cocfficients.

## 1. Introduction

Over the last two decades great effort has been spent by econometricians. statisticians and system theorists on the problem of system identification. This problem is concerned with construction of a model whose output is close in some sense to the observed data from the real system. The modeler is guided by experience. knowledge of the real thing he is trying to describe, and intuition in specifying some equations (dynamic or static) which he terms the "structure" of the model. The equations are usually specified to within a number of parameters or coefficients which must be estimated by fitting the equations to the available data. The unk nown parameters are usually assumed a priori to be constant. Then the problem of system identilication is reduced to one of constant parameter estimation. There is a wealth of methods for the solution of this problem. A good survey of the ones that have been developed by econometricians and statisticians can be found in Theil (1971), while Åström and Eykhoff (1971) have surveyed the methods that have been developed primarily in system theory.

There are se veral reasons for suspecting that the parameters of many models. constructed by both engineers and econometricians. are not constant but in fact time varying. In engineering the origins of parameter variation are ustally not very hard to pinpoint. Component wear metal fatigue or component failure are some very common reasons for parameter variations. The major objective of construction of engineering models is control and regulation of the real system

* Research supported by National Science Foundation Grant GJ-:154x to the National Bureat of Economic Research. Inc.: and by an M.I.T. endowed tellowship. This Research Report. WOOI? has not undergone the full critical review accorded the National Bureau's studies. including review by the Board of Directers.

I wish to acknowledge most valuable discussions with. and feedback from, Dr. Paul W. Holland of the NBER Computer Research Center. and Dr. J. Phillip Cooper of the University of Chicago. I retain sole responsibility for errors and omissions.
modeled. Therefore most of the reseateh in that area has concentated on devising ways to make the output of the model insensitive to parameter sariations

On the other hand the origins of time varying parameters in economenic models are not very easy to isolate. Suspicions that shocks in the economy lead to sometimes permanent changes in the parameters of ceonometric models. have been substantiated ever since it was noticed that models of the economy fitted with prewar data gate noticeably different parameters than when fitted with postwar data. Howerer if one examines the process of ceonomic modeling he will see several other sources of parameter variation. I will mention four of the most common ones.

Many econometric equations are mis-specified in the sense that they exclude variables that could possibly be part of the equation. Consider an equation of the form

$$
\begin{equation*}
y_{t}=\sum_{i=1}^{k} \beta_{i} x_{i t}+\sum_{j=1}^{\vdots} y_{j} z_{j t}+\varepsilon_{i} \tag{1}
\end{equation*}
$$

where $y$ is an endogenous variable and the $x_{i}$. $z_{i}$ are the true explanatory variables. If the coonometrician ignores the $z_{i}$ and lumps them with the error term i.. then whenever the $z_{j}$ s behave in a non-stationary faslioion there will be time variations in the intercept of (1).

Nonlinearities atso give rise to parameter variations. If. for instance, the true relation is:

$$
\begin{equation*}
y_{1}=x_{1}+x_{2} x_{1}+x_{3} x_{1}^{2}+x_{1} \tag{2}
\end{equation*}
$$

and the analyst considers the linear relation

$$
\begin{equation*}
y_{t}=\beta_{1}+\beta_{2}, x_{t}+\varepsilon_{t} \tag{3}
\end{equation*}
$$

then
(4)

$$
\frac{\dot{y} y_{t}}{\dot{r x_{t}}}=\beta_{2 t}=\alpha_{2}+2 x_{3} \cdot x_{2}
$$

thus $\beta_{2 r}$ is not constant.
Finally proxy variables and aggregation are also sources of parameter tariation. For a detailed exposition of the sources of parameter variation the reader is referred to Cooley (1971).

This paper is concerned with a Bayesian method of estimatien of time varying parameters. In section 2 a survey of previous research is given. The problem posed here is described in seetion 3. In sections 4 through 6 the method proposed for parameter estimation is presented and the properties of the estimator a malysed. Sections 7 and 8 consider some problems that arise in applying the estimation technique. In section 9 the question of identifiability of a particular Markor structure is taken up, and a Bayesian solution which is the only feasible one is proposed. The last section summarizes the results.

## 2. Previous Research on Estimation of Time Varying Parameters

The problem of estimation of tume varying parameters has not received very much attention from ceonometricians. On the other hand system theorists have
devoted many years of research to various aspects of it. The reasons for this apparent gap will become clearer later

The model from this point on will be assumed to be linear in the parameters. The following three classes of non-constant parameters are distinguished
(a) Time varying but non-stochastic
(b) Random but stationary
(c) Random but not necessarily stationary.

The earliest time varying parameter in econometrics dealt with parameters that were piecewise constant (Quandt (1958. 1960)) namely in class (a). This work was continued later by McGee and Carleton (1970), Brown and Earbin (1971) and Belsley (1973) but is still far from solved.

The second class of varying coefficients mentioned above applies to many problems in econometrics and statistics. and especially to the analysis of crosssectional data. The problem is usually posed in terms of a relation of the form

$$
\begin{equation*}
y_{t}=\sum_{i=1}^{k} \beta_{i t} x_{i t}+\varepsilon_{t} \tag{5}
\end{equation*}
$$

where at each period $t$ the parameters $\beta_{\text {it }}(i=1 \ldots, k)$ are a sample from a mult $i$ variate distribution with mean $\mu$ and covariance matrix $\Sigma$. The objective is usually to estimate $\mu$ and $\Sigma$. Work on this problem has been done by Rao (1965), Hildreth and Houck (1968). Burnett and Guthrie (1970). Swamy (1970). and Rosenberg (1972).

Under the third category mentioned above come the various sequential variation models of the form

## (6)

$$
\beta_{t+1}=T \beta_{i}+u_{t} .
$$

This model is very common in the engineering literature and can be utilized to represent a wide variety of sample paths. In the econometrics literature to my knowledge only Rosenberg (1967, 1968a, b) has dealt extensively with this kind of sequential variation. Cooley (1971) has also used it. mainly as a predictive tool.

On the other hand the engineering literature on estimation of models of the form (6) is huge. The earliest work was the one by Kaiman and Bucy (1961). For extensive bibliographies and various aspects of the problem the reader can consult the textbooks of Sage and Melsa (1971). and Aström (1970) as well as the special issue of the IEEE (1971) Transactions on Automatic Control.

In most of the engineering literature the statistics of the uncertain quantities are assumed known. This is a severe restriction when one is transferred to the realm of statistics and econometrics and is one of the primary reasons for which there is a large gap bet ween research in system theory and the quantitative social sciences. Interesting exceptions to the rule in the engineering literature are the papers by Mehra (1970, 1971, 1972). and Kasinyap (1970). Furthermore. the engineers usually make strong a priori assumptions about the matrix $T$, which as will be seen in section 9 do not. in general. hold in an econometric framework.

## 3. Problem Description

Consider the following model

$$
y_{t}=x_{t} \beta_{t}+\varepsilon_{t}
$$

where $y$, is the response to the effects of the $k$ explatatory variables $x_{1}, x_{2}, \ldots$ $x_{k l}, x_{t}$ is a $1 \times k$ vector of the mentioned explanatory variables, $\beta_{t}$ is a $k \times 1$ vector of time varying coefficients. and $\delta$ is a disturhance term that is assumed to be normally distributed with the following properties.

$$
\begin{align*}
E\left[\varepsilon_{i}\right] & =0  \tag{8}\\
E\left[\psi_{i}^{2}\right] & =\sigma_{\varepsilon}^{2}  \tag{9}\\
E\left[r_{1}, c_{i}\right] & =\sigma_{\varepsilon}^{2} j_{k 1}  \tag{10}\\
E\left[\varepsilon_{i}, \beta_{1}\right] & =0 \tag{11}
\end{align*}
$$

where $\delta_{k l}$ is the Kronecker delta. and $\sigma_{\varepsilon}^{2}$ is an unknown constant. The assumption is that there are $N$ observations on the endogenous variable $y$ and the $k$ exogenous variables.

Define the following quantities
where (') denotes the transposition.

$$
\begin{gather*}
\beta=\left[\beta_{1}^{\prime}, \beta_{2}^{\prime} \ldots \ldots, \beta_{\mathrm{v}}\right]^{\prime}  \tag{13}\\
\varepsilon=\left[\varepsilon_{1}, \varepsilon_{2}, \ldots, \varepsilon_{\mathrm{N}}\right]^{\prime}  \tag{14}\\
X=\left[\begin{array}{ccccc}
x_{1} & 0 & \ldots & 0 \\
0 & x_{2} & \ldots & 0 \\
\vdots & & & \\
0 & & & x_{\mathrm{N}}
\end{array}\right] . \tag{15}
\end{gather*}
$$

The available information now can be written as follows:

$$
y=x \beta+\varepsilon
$$

It can be readily seen now that it is impossible to estimate the vector $\beta$ (a $N k \times 1$ vector) from (16). via ordinary least squares (OLS) regression. To use the OLS formula the matrix $X X$ must be invertible. It is easily seen, however, that this $N k \times N k$ matrix has rank at most equal to $N$. So there are not enough degrees of freedom to estimate $\Omega$.

The conciusion from the above discussion is that there is no hope of estimating $\beta$ unless some more information about the vector becones available. I will assume that the $\beta_{i}$ 's can be generated by a Markovian structure of the form

$$
\begin{equation*}
\beta_{t+1}=T \beta_{r}+u_{t+1} \quad(t=0,1 \ldots, N-1) \tag{17}
\end{equation*}
$$

where: $T$ is a known $k \times k$ transition matrix and $u_{j}$ is a $k \times 1$ vector of random shocks distributed as multivariate normal with zero mean and covariance matrix (18)

$$
E\left[u_{i} u_{k}\right]=\sigma_{u}^{2} R \delta_{k j}
$$

where $R$ is a known $k \times k$ positive semidefinite matrix
The vector $\beta_{0}$ will be assumed unknown.

