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Estimation of Dynamic Models With Error Components

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of the initial operation. After this, the model and its associated assumptions are presented in detail. In this paper, we consider the properties of the initial operation, and the focus will be on the interpretation of these properties under various assumptions. The models arising from different assumptions about the initial operation may differ, and we must consider a number of different models. When the model and its associated assumptions are derived, the interpretations of these models are presented in detail. In this paper, we consider the properties of the initial operation, and the focus will be on the interpretation of these properties under various assumptions. The models arising from different assumptions about the initial operation may differ, and we must consider a number of different models. When the model and its associated assumptions are derived, the interpretations of these models are presented in detail. In this paper, we consider the properties of the initial operation, and the focus will be on the interpretation of these properties under various assumptions. The models arising from different assumptions about the initial operation may differ, and we must consider a number of different models. When the model and its associated assumptions are derived, the interpretations of these models are presented in detail. In this paper, we consider the properties of the initial operation, and the focus will be on the interpretation of these properties under various assumptions. The models arising from different assumptions about the initial operation may differ, and we must consider a number of different models. When the model and its associated assumptions are derived, the interpretations of these models are presented in detail. In this paper, we consider the properties of the initial operation, and the focus will be on the interpretation of these properties under various assumptions. The models arising from different assumptions about the initial operation may differ, and we must consider a number of different models. When the model and its associated assumptions are derived, the interpretations of these models are presented in detail.
leads to infinity or 0 tends to infinity or both. Furthermore, the
density of the joint, multivariate normally distributed when in
the are exogenous, heteroscedastic and Gaussian, and
independent of the maximum likelihood estimator (MLE) of  \( \theta > 0 \) and  \( \lambda > 0 \),

\[
\begin{align*}
\frac{1}{N} \sum_{t=1}^{N} \mathbf{y}_t^\top \mathbf{Y}_t^{-1} \mathbf{y}_t &= \hat{\Sigma}_y \\
\end{align*}
\]

we obtain the covariance estimator (Cov) or \( \hat{\Sigma} \) and

\[
\hat{\Sigma} = \frac{1}{N} \sum_{t=1}^{N} \mathbf{y}_t^\top \mathbf{Y}_t^{-1} \mathbf{y}_t 
\]

\[
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\]

from the density function of the exact likelihood function of \( Y_t \). We can write

\[
\hat{\Sigma} = \frac{1}{N} \sum_{t=1}^{N} \mathbf{y}_t^\top \mathbf{Y}_t^{-1} \mathbf{y}_t
\]

where the consistence of the sample covariance matrix in the sample
is the model commonly used in the empirical research of a sample

\[
\hat{\Sigma} = \frac{1}{N} \sum_{t=1}^{N} \mathbf{y}_t^\top \mathbf{Y}_t^{-1} \mathbf{y}_t
\]
\[ \nabla_X + (\gamma - t^{-1} - 1) \lambda g = (\lambda - \nabla_X) \] (2.7)

To see this, we can rewrite (2.6) as

\[ (\theta - t) \Lambda \] and Equation (2.1) in the form of Equation (2.6).

The assumption of the cross-section model implies that the estimated levels are observed through constants (assumption 1.95). The assumption (2.6) is a consequence of this assumption. Therefore, if the estimated levels are observed through constants, then the estimated levels are observed through constants.

\[ (\theta - t) \Lambda \] and the estimated levels are observed through constants.

The estimated levels are observed through constants.

From (2.6), we also assume that

\[ \sum_{i=1}^{N} I_{i} = 1 \] and that the mean of the observed variables

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Instead of (2.4), we have

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In this paper, we shall focus on the interpretation of the model and the asymptotic properties of the score estimates. When the interpretation of the model is also not independent of our assumptions, the problem becomes

\[ \sum_{i=1}^{N} I_{i} = 1 \] and the estimated levels are observed through constants.

The estimated levels are observed through constants.
We may assume that $\kappa_{Y_0}$ is a random draw from a population without the linear relationship.

The actual model we consider is the: $\kappa_{Y_0}$ as the initial observation, $\kappa_{Y_0}$ as the model, and $\kappa_{Y_0}$ as the error term. The random variable $\kappa_{Y_0}$ is independent of the starting value $\kappa_{Y_0}$.

In the model (2.9) and (2.10), alternative standard assumptions are:

\begin{align*}
\sum_{i=0}^{n-1} \gamma_i &= \gamma \quad (2.9) \\
\sum_{i=0}^{n-1} \gamma_i &= \gamma \quad (2.10)
\end{align*}

We may rewrite (2.9) as:

(2.9) (2.10)

And then determine the event:

The estimated effects are not shown. The model at time $t$, but are determined independently of the starting value $\kappa_{Y_0}$.

It may be inadvisable to assume $\kappa_{Y_0}$ as fixed components because $\kappa_{Y_0}$ represents effects not taken into account explicitly.

Since $\kappa_{Y_0}$ represents effects not taken into account explicitly, it may be inadvisable to assume $\kappa_{Y_0}$ as fixed components because $\kappa_{Y_0}$ represents effects not taken into account explicitly.
Least squares estimation of $\beta$ to the model

We note that $\hat{\beta}^T X \approx \beta^T X$.

$[T^{-1} \beta^T X - T^{-2} \beta^T X^2] \approx \beta^T X$ \hspace{1cm} \text{(3.7)}$

\text{Let } \xi = \beta^T X, \text{ and } \xi_0 = \text{fixed component and observable such that}$

In this section we assume that the initial observations $X_0$ are

\text{fixed initial observations}$

Eventually reaches a level of $[\gamma, \gamma + \gamma_0]$, and then, at time zero, the effect of initial endowment components and

\text{No initial fixed}$

\text{We may let}$

\text{If we want to assume that the initial endowment affects the vector of random draws from a population with mean } \mu \text{ and variance } \sigma^2 \text{, then now the initial observables value is not a fixed constant but a random variable, except in which the starting value and the vector } X_0 \text{ are independent, except for the treatment variables, and eventually the initial vector } X_0 \text{ and the initial observation } Y_0 \text{ is independent of } X_0 \text{ and } Y_0 \text{, its impact independently.}

For instance, if we assume $Y_0$ to be random with mean zero and variance $\sigma^2$, the impact of initial endowment will be different at these levels. For the treatment of initial endowment is different from the assumptions about $\xi_0$, then we may say that $\xi_0$ represents the effect of initial endowment.
\[
\left(\begin{array}{cccc}
\gamma + 1 & 1 & 1 & 1 \\
\vdots & \vdots & \vdots & \vdots \\
1 & 1 & \gamma + 1 & 1 \\
1 & 1 & 1 & \gamma + 1 \\
\end{array}\right) = \frac{1}{\gamma} I_N
\]

where

\[
g_t = \frac{\gamma - 1}{\gamma} - \frac{1}{\gamma} I_N
\]

and

\[
\left| v \right| \left| \log \frac{c}{\delta} \right| \left| \log \frac{\delta}{\gamma} \right| \left| \log \frac{\gamma}{\delta} \right| = 1
\]

The joint distribution as

If \( \gamma \) are normally distributed, we can write down the joint distribution of

and

but we assume that \( \gamma \) are normally distributed. In this

which is not equal to zero.

\[
\frac{\gamma}{\gamma + 1} - 1 = \frac{1}{\gamma}
\]

The joint distribution of

\[
\left(\frac{\gamma - 1}{\gamma} - 1, \frac{1}{\gamma} I_N\right)
\]

is

\[
\left(\begin{array}{cccc}
\gamma + 1 & 1 & 1 & 1 \\
\vdots & \vdots & \vdots & \vdots \\
1 & 1 & \gamma + 1 & 1 \\
1 & 1 & 1 & \gamma + 1 \\
\end{array}\right) = \frac{1}{\gamma} I_N
\]

where

\[
0 = \frac{1}{\gamma} I_N
\]

As a law of large numbers

Therefore, when \( \gamma \) tends to infinity, we can prove the consistency and asymptotic normality of the coefficient estimator in exactly the same form as that of

where

\[
\left(\frac{\gamma - 1}{\gamma} - 1, \frac{1}{\gamma} I_N\right)
\]

is

\[
\left(\begin{array}{cccc}
\gamma + 1 & 1 & 1 & 1 \\
\vdots & \vdots & \vdots & \vdots \\
1 & 1 & \gamma + 1 & 1 \\
1 & 1 & 1 & \gamma + 1 \\
\end{array}\right) = \frac{1}{\gamma} I_N
\]

the joint distribution of

\[
\left(\frac{\gamma - 1}{\gamma} - 1, \frac{1}{\gamma} I_N\right)
\]

is

\[
\left(\begin{array}{cccc}
\gamma + 1 & 1 & 1 & 1 \\
\vdots & \vdots & \vdots & \vdots \\
1 & 1 & \gamma + 1 & 1 \\
1 & 1 & 1 & \gamma + 1 \\
\end{array}\right) = \frac{1}{\gamma} I_N
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where

\[
\left(\frac{\gamma - 1}{\gamma} - 1, \frac{1}{\gamma} I_N\right)
\]
To show that the MLE is consistent when \( N \) tends to infinity and

\[ 0 = \left( \theta \mathbf{1} \right)^{\top} \mathbf{1} \left( \mathbf{X} \right)^{\top} \mathbf{1} \mathbf{X} \mathbf{X}^{\top} \mathbf{1} \mathbf{1}^{\top} \mathbf{X} \mathbf{X} \left( \theta \mathbf{1} \right) - \frac{\mathbf{1}^{\top} \mathbf{1}}{N} \mathbf{1} \mathbf{1}^{\top} \mathbf{1} \mathbf{1} \mathbf{1}^{\top} - \frac{\mathbf{1}^{\top} \mathbf{1}}{N} \mathbf{1} \mathbf{1}^{\top} \]
\[ \frac{1}{T} \sum_{i=1}^{T} \left( \frac{\beta}{1+\gamma} \right)^{\frac{1}{2}} \frac{Z_i}{\left(1+\gamma\right)^{\frac{1}{2}}} = \left( \frac{\beta}{1+\gamma} \right)^{\frac{1}{2}} \frac{\bar{Z}}{\left(1+\gamma\right)^{\frac{1}{2}}} \]

The joint density of \( \omega \) and \( \eta \) is given by
\[
\frac{1}{\sqrt{2\pi}} \exp \left\{ -\frac{1}{2} \left( \frac{(\omega - T)^2}{\sigma^2} + \frac{\eta^2}{\tau^2} \right) \right\}
\]

The random vectors \( \omega \) and \( \eta \) are jointly normally distributed with zero mean and covariance matrix \( \Sigma \). A convenient form for the determinant of \( \Sigma \) is given by
\[
\det(\Sigma) = \prod_{i=1}^{n} \lambda_i
\]

In this section, we consider the second model of a random vector, which is independent of a standard normal vector. Furthermore, the determinant of the covariance matrix of \( \omega \) and \( \eta \) is given by
\[
\det(\Sigma) = \prod_{i=1}^{n} \lambda_i
\]

The random vector is defined as
\[
\omega = \left[ \begin{array}{c} \left( \frac{\beta}{1+\gamma} \right)^{\frac{1}{2}} \frac{Z_1}{\left(1+\gamma\right)^{\frac{1}{2}}} \\ \vdots \\ \left( \frac{\beta}{1+\gamma} \right)^{\frac{1}{2}} \frac{Z_T}{\left(1+\gamma\right)^{\frac{1}{2}}} \end{array} \right]
\]

Furthermore, the determinant of \( \Sigma \) is given by
\[
\det(\Sigma) = \prod_{i=1}^{n} \lambda_i
\]

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\[
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\]

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\[
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\]
\[
\begin{aligned}
\mathcal{O}_{Y}(x + t) &= \frac{(g - t)(t - \lambda + \chi) + z}{N} + \mathcal{O}_{Y}(x + t) \quad \text{for} \quad t > 0,
\end{aligned}
\]
\[
\begin{pmatrix}
1 & \cdots & \frac{g-1}{l} \\
\vdots & \ddots & \vdots \\
\frac{g-1}{l} & \cdots & 1
\end{pmatrix} + \begin{pmatrix}
1 & \cdots & 0 \\
\vdots & \ddots & \vdots \\
0 & \cdots & 1
\end{pmatrix} = I
\]

(5.9)

where

\[
\begin{pmatrix}
I \\
\vdots \\
I
\end{pmatrix} = \begin{pmatrix}
\frac{g-1}{l} \\
\vdots \\
\frac{g-1}{l}
\end{pmatrix},
\]

\[
\begin{pmatrix}
0 \\
\vdots \\
0
\end{pmatrix} = \begin{pmatrix}
\frac{g-1}{l} \\
\vdots \\
\frac{g-1}{l}
\end{pmatrix}
\]

but the boundary solution of \( Y = 0 \) or \( 0 = 0 \) cannot occur.

The boundary solution of \( Y = 0 \) or \( 0 = 0 \) cannot occur.

There are similar conditions for the occurrence of boundary

\[
\text{is no indeterminant parameters problem in this case.}
\]

\[
(1)^T x^T \begin{pmatrix}
\frac{g-1}{l} \\
\vdots \\
\frac{g-1}{l}
\end{pmatrix} + (1)^T \begin{pmatrix}
\frac{g-1}{l} \\
\vdots \\
\frac{g-1}{l}
\end{pmatrix} = 0
\]

\[
\text{are random vectors. Then, there is no indeterminant parameters problem in this case.}
\]

\[
\begin{pmatrix}
\frac{g-1}{l} \\
\vdots \\
\frac{g-1}{l}
\end{pmatrix} \text{ are random.}
\]

\[
\text{with arbitrary variance} (\Omega) \text{ case} (a) \text{ does not simplify the case}
\]

\[
\Omega \text{ have to be used. Unfortunately, the assumption that} \text{ a random}
\]

\[
\text{do not have a simple solution and a completely satisﬁed scheme with}
\]

\[
(\Omega) \text{-} (\Omega) \text{ case}
\]

\[
\text{independent of the way of } X \text{ or } N \text{ goes to inﬁnity}.
\]

\[
\text{However,} (\Omega) \text{-} (\Omega) \text{ case}
\]

\[
\text{is consistent and}
\]

\[
\text{although the consistency of the} \text{ is not independent of the}
\]

\[
\epsilon = + \text{ and is inconsistent as } N \to \infty.
\]

\[
\text{consistent at } p \text{ and is inconsistent as } N \to \infty.
\]

\[
\epsilon = + \text{ and is inconsistent as } N \to \infty.
\]

\[
\text{when } N \text{ tends to inﬁnity and } \epsilon \text{ is the result of}
\]

\[
\text{the result of}
\]

\[
\text{the result of}
\]

\[
\text{the same for both } X \text{ and } Y \text{ random with a symmetric distribution.}
\]

\[
\text{the same for both } X \text{ and } Y \text{ random with a symmetric distribution.}
\]

\[
\text{the result of}
\]

\[
\text{when } N \text{ tends to inﬁnity, the consistency of}
\]

\[
\epsilon = + \text{ and is consistent as } N \to \infty.
\]

\[
\text{consistent at } p \text{ and is inconsistent as } N \to \infty.
\]

\[
X = \begin{pmatrix}
T & T \\
\vdots \\
T
\end{pmatrix}
\]

\[
\text{are random vectors. Then, there is no indeterminant parameters problem in this case.}
\]

\[
\begin{pmatrix}
\frac{g-1}{l} \\
\vdots \\
\frac{g-1}{l}
\end{pmatrix} \text{ are random.}
\]

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\text{with arbitrary variance} (\Omega) \text{ case} (a) \text{ does not simplify the case}
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\[
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\]

\[
\text{consistent at } p \text{ and is inconsistent as } N \to \infty.
\]

\[
\epsilon = + \text{ and is inconsistent as } N \to \infty.
\]
\[
\lambda_0, \ldots, \lambda_t = \lambda, \quad \lambda_0 = \frac{\mu_0 g Z}{N}, \quad \frac{\mu_0 g Z}{N} = \frac{\mu_0 g Z}{N} = \lambda_0
\]

With respect to \( \lambda_0 \), and these are

\[
\frac{\lambda}{\mu} \cdot \frac{\lambda}{\mu} \cdot \frac{\lambda}{\mu}
\]

\[
\lambda_0 = \frac{\mu_0 g Z}{N} = \frac{\mu_0 g Z}{N} = \frac{\mu_0 g Z}{N} = \lambda_0
\]

The ME is still consistent if either \( \lambda \) tends to infinity and \( \lambda_0 \) tends to infinity, but the computation is then complicated.
\[ \frac{N}{\sum^t(0T_A + 0T_X - t^{-T}T_A)} = \frac{N}{\sum^t(0T_A + 0T_X - t^{-T}T_A)} \]

\[ \frac{(0T_A + 0T_X - t^{-T}T_A)}{\sum^t(0T_A + 0T_X - t^{-T}T_A)} = \frac{N}{\sum^t(0T_A + 0T_X - t^{-T}T_A)} \]
In this section we first consider the model (2.1.1) where the

Random Initial Observations with a Common Mean

If , we may be interested to note that when = 1, this is similar

The assumption of the behavior of the CP processes in the two

This contradiction shows that is not consistent.

\[ \lambda \hat{H}(\theta - 1) = \frac{\hat{H} \theta - 1}{\hat{H} \theta - 2} \]

If is not equal to zero, it is equal to

The probability that the difference directed by is

Based on the results, if is consistent, we can replace it by and the

In general, we support the right-hand side from the left-

and that converge to a finite consistent, we solve (4.6) and

These results maximize yields a consistent point. To show this, we assume

maximize; but none can give an absolute maximum. Neither does any of

These properties of the t-test function! Moreover, these results

Finalize, and we derive the essential difference solutions, there give

the (9, 6) into (5, 6) and (5, 7) to obtain three polynomial equations in

Now let us consider the case of . If we substitute (5, 12)
We note that the conditions on \( T \) and \( \sigma \) are more restrictive in the case of the moment matrix compared to the moment matrix of the conditional moment function. This is because the moment function is constructed from the conditional moment function with respect to \( \theta \), and as a result, the conditions on \( T \) and \( \sigma \) are more stringent.

In the case of the moment matrix, we have

\[
0 = \left( c - 0^{1} T X \right) \frac{1}{N} \frac{\sigma^{2}}{T^2} + \left( c + T^{1} X g - (0^{1} T X - 0^{2} T X) \right) \frac{1}{N} \frac{\sigma^2}{(T+1)^N} - \frac{\sigma^2}{T^2 \log T} \tag{6.9}
\]

and

\[
0 = \frac{1}{N} \left( c + T^{1} X g - (0^{1} T X - 0^{2} T X) \right) \frac{1}{N} \frac{\sigma^2}{(T+1)^N} - \frac{\sigma^2}{T^2 \log T} \tag{5.9}
\]

We can rewrite the conditions on \( T \) and \( \sigma \) as

\[
\begin{pmatrix}
Y + T \\
\vdots \\
T + \cdots \\
T + \cdots \\
\end{pmatrix} \cdot \begin{pmatrix}
(T+1)^N \\
(T+1)^N \\
(T+1)^N \\
(T+1)^N \\
\end{pmatrix}
\]

where

\[
0 = \left( c - 0^{1} T X \right) \frac{1}{N} \frac{\sigma^2}{T^2} + \left( c + T^{1} X g - (0^{1} T X - 0^{2} T X) \right) \frac{1}{N} \frac{\sigma^2}{(T+1)^N} - \frac{\sigma^2}{T^2 \log T} \tag{6.9}
\]
Theorem \((7.4)\)

\[
X^T X - I \rightarrow I, \\
X^T Y - I \rightarrow I
\]

is normally distributed with mean 0 and covariance matrix

\[
\begin{pmatrix}
0 & \ldots & 0 \\
\vdots & \ddots & \vdots \\
0 & \ldots & 0
\end{pmatrix}
\]

and a constant variance of \(\sigma^2\). This result can either be used to construct an estimator of \(\beta\) or a constant term. The solution can either be used, or the least squares regression of

\[
0 = [\omega + T^{-1} \hat{\beta}_Y - (\hat{\beta}_Y^T X) \beta] X^T Y + \frac{\sigma^2}{N} + \frac{\sigma^2}{N} = \frac{\sigma^2}{N} (10.6)
\]

Then

\[
0 = T^{-1} \hat{\beta}_Y - (\hat{\beta}_Y^T X) \beta = \frac{\sigma^2}{N} (10.6)
\]

or

\[
0 = T^{-1} \hat{\beta}_Y - (\hat{\beta}_Y^T X) \beta = \frac{\sigma^2}{N} (10.6)
\]

or

\[
0 = T^{-1} \hat{\beta}_Y - (\hat{\beta}_Y^T X) \beta = \frac{\sigma^2}{N} (10.6)
\]
distributed random vectors, the $j$-th having density $f_0 X_j$ (the $i$-th fixed) we are maximizing, i.e.,

$$\text{maximize } g \prod_{i=1}^{N} f_{0} X_i$$

and the rest of the integrals. This follows from the fact that conditional on $X_i$, the conditional density of $X_j$ over $i$ does not affect the result of the integration of the joint density of $X_i$.

Hence, it is independent.

Now consider $g = \prod_{i=1}^{N} f_{0} X_i$.

The probability that all the pseudo $M^2$ are equal to 1 is

$$\frac{1}{(\sum_{i=1}^{N} f_{0} X_i)} \left( \frac{1}{(\sum_{i=1}^{N} f_{0} X_i)} \right)^{N-1} \prod_{i=1}^{N} f_{0} X_i$$

The determinant of the $N \times N$ matrix\newline
\begin{align*}
&\left[\begin{array}{c}
(1 X_i - 1 X_j) (1 X_i - 2 X_j) \\
(2 X_i - 1 X_j) (1 X_i - 2 X_j) + 2 (1 X_i - 1 X_j) (2 X_i - 2 X_j) \\
(1 X_i - 2 X_j) (2 X_i - 2 X_j) + (1 X_i - 1 X_j) (2 X_i - 2 X_j)
\end{array}\right] \prod_{i=1}^{N} f_{0} X_i
\end{align*}

is equal to $\prod_{i=1}^{N} f_{0} X_i$.

We have

Taking partial derivatives of (7.7) with respect to $g$ and solving for $g$,

$$\text{det} \left[ \begin{array}{ccc}
(1 X_i - 1 X_j) (1 X_i - 2 X_j) & (1 X_i - 1 X_j) (2 X_i - 2 X_j) \\
(2 X_i - 1 X_j) (1 X_i - 2 X_j) & (2 X_i - 1 X_j) (2 X_i - 2 X_j) + (1 X_i - 1 X_j) (2 X_i - 2 X_j)
\end{array} \right] \prod_{i=1}^{N} f_{0} X_i = 0$$

Hence, by the maximization of the pseudo likelihood function $g$, the determinant of the $(N-1) \times (N-1)$ matrix

$$\text{det} \left[ \begin{array}{ccc}
(1 X_i - 1 X_j) (1 X_i - 2 X_j) & (1 X_i - 1 X_j) (2 X_i - 2 X_j) \\
(2 X_i - 1 X_j) (1 X_i - 2 X_j) & (2 X_i - 1 X_j) (2 X_i - 2 X_j) + (1 X_i - 1 X_j) (2 X_i - 2 X_j)
\end{array} \right] \prod_{i=1}^{N} f_{0} X_i = 0$$

is not affected by the mean zero and variance-covariance matrix $\Sigma$.

Thus, we have

$$\text{det} \left[ \begin{array}{ccc}
(1 X_i - 1 X_j) (1 X_i - 2 X_j) & (1 X_i - 1 X_j) (2 X_i - 2 X_j) \\
(2 X_i - 1 X_j) (1 X_i - 2 X_j) & (2 X_i - 1 X_j) (2 X_i - 2 X_j) + (1 X_i - 1 X_j) (2 X_i - 2 X_j)
\end{array} \right] \prod_{i=1}^{N} f_{0} X_i = 0$$

and $\Sigma = 0$. Then

maximize the likelihood estimates by considering the case where $X_i$ are fixed.

Intuitively, we show that the conditional density of these pseudo $M^2$ is normally distributed with mean zero and variance-covariance matrix

$$\Sigma = \left[ \begin{array}{ccc}
1 & \ldots & 1 \\
\vdots & \ddots & \vdots \\
1 & \ldots & 1
\end{array} \right]$$

Substitute (7.9) into the density of $\prod_{i=1}^{N} f_{0} X_i$ and de-
estimation, the does suggest some simple consistent estimators. From (7.9),

Although the maximization of (7.9) does not yield consistent

6. Simple Consistent Estimators

consistency of the conditional MLE (1.2, Chapter 9). The (1979), the

consistency of the conditional threshold function which causes the conditional about the

is inconsistent, we suggest that this procedure about the proper form

when is treated and is tends to infinity. It is the period in which

which is positive definite. Therefore, the conditional MLE is consistent

\[
\begin{pmatrix}
\theta (\lambda + T) \\
0
\end{pmatrix}
+ \left( \begin{pmatrix}
\theta \\
\lambda
\end{pmatrix}
\right) \begin{pmatrix}
\frac{T-1}{N} \\
\frac{T}{\lambda}
\end{pmatrix}
= \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]  

(7.7.1)

\[\begin{pmatrix}
\Lambda \\
0
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right) \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} \]  

(7.7.2)

\[\left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right) = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.3)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.4)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.5)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.6)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.7)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.8)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.9)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.10)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.11)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.12)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.13)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.14)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.15)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.16)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.17)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.18)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.19)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.20)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.21)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.22)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.23)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.24)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.25)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.26)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.27)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.28)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.29)

\[\begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix} = \left( \begin{pmatrix}
\frac{\Lambda}{1} \\
\frac{0}{1}
\end{pmatrix}
\right)
\]

(7.7.30)
The process to obtain the more efficient WRF.

In the estimation of quantities as the initial value to start the iteration,
know the correct choice of the initial conditions, we can always use the
although less efficient, does have the merit. Furthermore, if we
what the initial conditions are, thus, the instrumental variable method

Provided in making a correct choice of the initial conditions. Parameter
may be incorrect, but if we have multiple information to
be incorrect, insufficient, insufficient we have little information to
obtain the WRF. Misleading one case for the other in general will not lead
to incorrect analysis. Consider the transformation of the initial conditions. Different
assumptions about the initial conditions can lead to different methods.
WRF depend critically on the assumptions of the initial conditions. Different
assumptions about the initial conditions can lead to different methods.
But only over a shorter period of time, as it turns out, the properties of the
however, a typical partial wafer initially a small number of instruments,

Therefore, there are different assumptions about the initial observations

Potentially correlated and use (2.8) are consistent when in tends to infinity or T

Without knowledge of g, if there is little to choose between these

Therefore, (2.8) is preferred to (2.9)
In Section 6, although it is less efficient, it does have the advantage of being non-parametric. However, it is true that simple instrumental variable methods are therefore suggested.

It should be noted that the method of obtaining the NIE is different for the transformed model. This is because the initial observation and apply the least squares regression to the transformed model. We only need to modify the dependent variable to the mean, and effect the structural equation (Section 6), the conditional mean, and affect the estimation of initial conditions.

Conclusions

In this paper we have studied the problems of estimating a dynamic model with error components in panel with many either the number of time periods and the number of cross-sectional units.
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</tr>
</tbody>
</table>

The table lists the conditions under which the specification may or may not affect the interpretation of the results. For the mean, the effect of other operations is considered, with a cross-sectional unit.

**Table 1**
REFERENCES

-10-

Footnotes