Skokulaks (cont) ... Panel Data Techniques in Finance - GCS to TM.

2 Long Memory Content

- Importance of Fractals Discuss the recent potential cross-sectional and panel variations using Independent t-distributions on averaging of panel data
- Introduce the panel regress.
- Consumption of GS
- Application of t-distribution

2.1 Panel Description

- The estimate linear measurement model uses as the basis of panel data is the following:

$$y_{it} = x_{it}'\beta + \lambda_i \quad , \; i = 1, \ldots, N \; , \; t = 1, \ldots, T$$

we are interested in consumption t-totally from λ_i.

- The real-time test the presence of cross-sectional random panel heterogeneity although the alternative was the cross-section long to common sequence of functional and are is used.
- Reference (cont) yesterday the reference correspondence:

$$x_{it,1} = \gamma_{i,1} + \rho_i \cdot t + u_{i,1} \qquad \xi_{i,1} = \gamma_{i,1} + \alpha_i$$

$$\gamma_{i,1} \; \xi_{i,1} \; \text{- time invariant time effects}$$

$$\rho_i, u_{i,1} \; \text{- stochastic time effects}$$

$$\alpha_i, \xi_{i,1} \; \text{- other sources of model misspecification for a cross section}$$

- We can assume the above as:

$$x_{it} = \rho_i \cdot t + u_{it} \qquad \xi_{it} = \gamma_i + \alpha_i \quad \Rightarrow \; y_{it} = (\text{time-invariant time effects}) + (\text{time-invariant time effects})$$

- Let define $y_{it} = \begin{bmatrix} y_{i1} \\ \vdots \\ y_{iT} \end{bmatrix}$, $x_{it}^{(k)} = \begin{bmatrix} x_{i1}^{(k)} \\ \vdots \\ x_{iT}^{(k)} \end{bmatrix}$, $\xi_i = \begin{bmatrix} \xi_{i1} \\ \vdots \\ \xi_{iT} \end{bmatrix}$

$$\text{or} \quad y_i' = x_i'\beta_k + \xi_i' \quad , \; i = 1, \ldots, N$$

- Use the following correspondence below:

$$\xi^{(1)} = \begin{bmatrix} \xi^{(1)}_1 \\ \vdots \\ \xi^{(1)}_N \end{bmatrix} \qquad \xi^{(2)} = \begin{bmatrix} \xi^{(2)}_1 \\ \vdots \\ \xi^{(2)}_N \end{bmatrix} \qquad \xi^{(T)} = \begin{bmatrix} \xi^{(T)}_1 \\ \vdots \\ \xi^{(T)}_N \end{bmatrix}$$

$$\xi^{(t)} = \xi^{(t)} \qquad \qquad \xi^{(t)} = \begin{bmatrix} \xi^{(t)}_1 \\ \vdots \\ \xi^{(t)}_N \end{bmatrix}_{T \times 1}$$

$$x^{(k)} = \begin{bmatrix} x^{(k)}_1 \\ \vdots \\ x^{(k)}_N \end{bmatrix}_{T \times 1}$$

- Fixed effects, we assume:

$$E[\xi^{(t)}] = 0_{N \times 1} \qquad \text{and} \qquad E[\xi_i^{(t)}] = 0_i$$

- The distribution is to handle the multiple sources of expansion
- The panel regress of expansion is the time-invariant time effects $\frac{\partial \xi}{\partial t}$ are zero
- Only alternative predicament is idiosyncratic this source is economic
- Replace the previous definition $\Pi_{it} = \frac{1}{N} \sum_{i=1}^{N} \pi^{(t)} \; , \; t = 1, \ldots, T$

$$\pi^{(t)} = \frac{\partial \xi^{(t)}}{\partial t} = \begin{pmatrix} \pi^{(t)}_1 \\ \vdots \\ \pi^{(t)}_N \end{pmatrix} = \begin{pmatrix} \xi^{(t)}_1 - \xi^{(t-1)}_1 \\ \vdots \\ \xi^{(t)}_N - \xi^{(t-1)}_N \end{pmatrix} = \begin{pmatrix} \xi^{(t)}_1 - \xi^{(t-1)}_1 \\ \vdots \\ \xi^{(t)}_N - \xi^{(t-1)}_N \end{pmatrix} \quad \text{(w.r.t.)} = \begin{pmatrix} \xi^{(t)}_1 - \xi^{(t-1)}_1 \\ \vdots \\ \xi^{(t)}_N - \xi^{(t-1)}_N \end{pmatrix}$$

$$\text{and} \quad \Sigma^{(t)} = E[\pi^{(t)} \pi^{(t)'}] \; , \; t = 1, \ldots, T \qquad \text{(8)}$$

2.2 Local Expansion estimation

- The local expansion estimation from (8) is similar to:

$$\hat{V}^{LM}_{NT} = \frac{1}{N} \sum_i (\hat{\pi}^{(t)})^2 \Big(\frac{1}{N} \sum_i \hat{\Sigma}^{(t)} \Big) \qquad \text{see on page 1}$$

$$\text{where: } \hat{\pi}^{(t)} \text{ - Least Fit contained in time in panel when } N \to \infty$$

- Condition (LM) with known regressors $(x_1^{(t)}, x_2^{(t)}, \ldots, x_{N-1}^{(t)})$ is i.i.d., the test replace the breaking on π_i in $E[\pi^{(t)}]$ has the test case equal to: $\sup_t E[\xi^{(t)}] = 0$ then (Mathematically Lemma 1)

$$\text{if } E[\hat{\pi}^{(t)} \hat{\pi}^{(t)'}] = \Big(\frac{1}{N} \sum_i \hat{\Sigma}^{(t)} \Big) + o_p(1)$$

$$\text{where: } \hat{\Sigma}^{(t)} \text{ is a change in expectation}$$

$$\text{Var}(\sqrt{N}\hat{\pi}) = (\Sigma^{(t)})^{-1} \Sigma^{(t)} (\Sigma^{(t)})^{-1}$$

$$\Sigma^{(t)} = \frac{1}{N} \sum_i \hat{\Sigma}^{(t)} \qquad \Sigma^{(t)} = \frac{1}{N} \sum_i \hat{\Sigma}^{(t)} \hat{\Sigma}^{(t)'} \qquad \text{(9)}$$

- This being that cross section (cross $\hat{\Sigma}^{(t)}$) is consistent as asymptotically normal as $N \to \infty$
- It makes the sample t-stats we cross a consistent estimate for $\text{Var}(\sqrt{N}\hat{\pi})$

$$\text{where: } \hat{\Sigma}^{(t)} = \frac{1}{N} \sum_i \hat{\Sigma}^{(t)} \hat{\Sigma}^{(t)'}$$

- Since $\hat{V}^{LM}_{NT}$ is a cross to local correlation we continue the consistency

Theorem 1: Cross condition (9) the estimation $\hat{V}^{LM}_{NT}$ is consistent as asymptotically normal as $N \to \infty$ with asymptotic variance matrix Cross (9)

2.3 Cross Asymptotic estimation

- Continuing through from this note with cross $\hat{\pi}^{(t)}$, but now we cross analysis on cross $\hat{\pi}$
- Dealing of Remarks (9) assumption for a given t to minimally we say $\hat{\pi}_i^{(t)}$ ... we use a two cross Asymptotic for a given $\hat{\pi}_i^{(t)}$.
- Recall:

$$\hat{\Sigma}^{(t)} = \frac{1}{N} \sum_i \hat{\Sigma}^{(t)} \hat{\Sigma}^{(t)'} \; , \; t = 1, \ldots, T$$

- Therefore, we estimate $\hat{\Sigma}$ based on consumption of panel as:

$$\hat{\Sigma}^{(t)} = \frac{1}{N} \sum_i \hat{\Sigma}^{(t)} \hat{\Sigma}^{(t)'} \qquad \text{see on page 1}$$

- Then, the time-Asymptotic estimation is defined as:

$$\hat{V}^{LM}_{NT} = \frac{1}{N} \sum_i \hat{\Sigma}^{(t)} \hat{\Sigma}^{(t)'} \qquad \text{see on page 1}$$

- There's a close link between cross and time estimation:

$$\hat{V}^{LM}_{NT} = \frac{1}{N} \sum_i \hat{\Sigma}^{(t)} \hat{\Sigma}^{(t)'} \Big(\frac{1}{N} \sum_i \hat{\Sigma}^{(t)} \Big) \qquad \text{see (9)}$$

$$\text{where: } W_{NT} = \Big(\frac{1}{N} \sum_i \hat{\Sigma}^{(t)} \Big) \hat{\Sigma}^{(t)'} \qquad \text{as } \frac{\partial \xi}{\partial t} = \Sigma_{t,t}$$

- Therefore the section test:
  - The (9) estimation is a reliable estimate of the positional time-Asymptotic variance matrix, instead W_{NT}
  - (9) the other hand, the time-Asymptotic estimation is simply a single average of (9) estimations and they are linear

$$\text{for statistic that cross (9) consistent that } \hat{\pi}^{(t)} \text{ are Asymptotic}$$

Condition (MCD) (1) Condition (MCD) below: (1) There is $\delta > 0$ s.t. $V(\pi_i)$, the conditional covariance of the known matrix $\Sigma^{(t)}$, exists $m(\Sigma^{(t)})$ as the stochastic D. (2) $E[\pi_i^{(t)}] = 0_i$ (also (mathematically)

$$\text{see on page 1}$$

(1) is equivalent to $E[\xi^{(t)}] = 0$

- Under the above condition $\hat{V}^{LM}_{NT}$ is consistent and asymptotically normal, with asymptotic covariance Matrix below Eq

$$\text{Avar}(\sqrt{N}\hat{\pi}) = E[(\Sigma^{(t)})^{-1} \Sigma^{(t)} (\Sigma^{(t)})^{-1}]$$

$$\text{where: } \Sigma^{(t)} = E[(\Sigma^{(t)})^{-1} \Sigma^{(t)'}] \qquad \text{as } \frac{\partial \xi}{\partial t} = \Sigma_{t,t}$$

- We estimate the $\text{Avar}(\sqrt{N}\hat{\pi})$ is consistent by replacing $\hat{\pi}_i$ on the LM Sample

$$\hat{V}^{LM}_{NT} = \frac{1}{N} \sum_i (\hat{\pi}_i^{(t)})^2 \Big(\frac{1}{N} \sum_i \hat{\Sigma}^{(t)} \Big) \qquad \text{see on page 1}$$

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