行政院國家科學委員會專題研究計畫 期中進度報告

貨幣、匯率與動態均衡之學術前沿研究--子計畫七：匯率預測：估計風險之角色(3/4)

期中進度報告(完整版)

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計 畫 主 持 人 ：郭炳伸

報 告 附 件 ：出席國際會議研究心得報告及發表論文

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Explanation for the Form of the <u>Annual/Midterm/Final</u> Report "Program for Promoting Academic Excellence of Universities（Phase II）"

※ The <u>Annual/Midterm/Final</u> Report contains the following sections:

I		COVER
II	**FORM1**	BASIC INFORMATION OF THE PROGRAM
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(Add extra lines or columns if needed.)

I. COVER

Program for Promoting Academic Excellence of Universities（Phase II）

Annual Report

匯率預測：估計風險之角色 (3/4)

Understanding Exchange Rate Predictability: The Role of Estimation Risk (3/4)

Serial number: NSC 95-2752-H-004 -002 -PAE

Overall Duration: Month ___04__ Year _2006_____ - Month _03____ Year__2010___

Report Duration: Month __04__ Year __2008___ Month _03___ Year__2009___

National Chengchi University

Jan., 2009

II. (FORM1) BASIC INFORMATION OF THE PROGRAM

Program Title: 匯率預測：估計風險之角色 (3/4) Understanding Exchange Rate Predictability: The Role of Estimation Risk (3/4)					
Serial No.: NSC 95-2752-H-004 -002 –PAE			Affiliation	(in English & Chinese)	
Principal Investigator	Name	郭炳伸 Biing-Shen Kuo	Program Coordinator	Name	(in English & Chinese)
	Tel:	(02) 29393091 ext 81029		Tel:	
	Fax:	(02) 29387699		Fax:	
	E-mail	bsku@nccu.edu.tw		E-mail	

	Expenditures[1] (in NT$1,000)		Manpower[2]:Full time/Part time(Person-Months)	
	Projected	Actual	Projected	Actual
FY 2006	1052	711	3	3
		-		-
		-		-
		-		-
Overall	1052	711	3	3

Serial No.	Project Title	Principal Investigator	Title	Affiliation
Sub-Project 7	匯率預測：估計風險之角色 Understanding Exchange Rate Predictability: The Role of Estimation Risk	郭炳伸 Biing-Shen Kuo	教授 Professor	國立政治大學國際貿易學系 National Chengchi Univ.

Notes: [1,2] Please explain large differences between projected and actual figures.

Program Director/Principle Investigator Signature: Biing-Shen Kuo

III. (FORM 2) LIST OF WORKS, EXPENDITURES, MANPOWER, AND MATCHING SUPPORTS FROM THE PARTICIPATING INSTITUTES（REALITY）.

Serial No.: **NSC 95-2752-H-004 -002 -PAE**	Program Title: 匯率預測：估計風險之角色 **Understanding Exchange Rate Predictability: The Role of Estimation Risk**											
Research Item (Include sub projects)	Major tasks and objectives	Expenditures (in NT$1,000)					Manpower (person-month)					Matching Supports from the Participating Institutes (in English & Chinese)
		Salary	Seminar/ Conference-related expenses	Project- related expenses	Cost for Hardware & Software	Total	Principal Investigators	Consultants	Research/ Teaching Personnel	Supporting Staff	Total	
Sub-project 7	Develop of new estimators and explore its applications	504	207	0	0	664	1	0	2	0	2	0
SUM		516	148	0	0	664	1	0	3	0	4	0

IV. (Form 3) Statistics on Research Outcome of this Program

Listing		Total	Domestic	International	Significant[1]	Citations[2]	Technology Transfer
Published Articles	Journals						
	Conferences						
	Technology Reports						
Patents	Pending				-		
	Granted				-		
Copyrighted Inventions	Item						
Workshops/Conferences[3]	Item	3	1	2			
	Participants	Around 80	Around 40	Around 40			
Training Courses (Workshops/Conferences)	Hours						
	Participants						
Personal Achievements	Honors/ Awards[4]						
	Keynotes Given by PIs						
	Editor for Journals						
Technology Transfers	Item						
	Licensing Fee						
	Royalty						
Industry Standards[5]	Item						
Technological Services[6]	Item				-	-	-
	Service Fee				-	-	-

[1] Indicate the number of items that are significant. The criterion for "significant" is defined by the PIs of the program. For example, it may refer to Top journals (i.e., those with impact factors in the upper 15%) in the area of research, or conferences that are very selective in accepting submitted papers (i.e., at an acceptance rate no greater than 30%). Please specify the criteria in Appendix IV.
[2] Indicate the number of citations. The criterion for "citations" refers to citations by other research teams, i.e., exclude self-citations.
[3] Refers to the workshop and conferences hosted by the program.
[4] Includes Laureate of Nobel Prize, Member of Academia Sinica or equivalent, fellow of major international academic societies, etc.
[5] Refers to industry standards approved by national or international standardization parties that are proposed by PIs of the program.
[6] Refers to research outcomes used to provide technological services, including research and educational programs, to other ministries of the government or professional societies.

V. (FORM4) EXECUTIVE SUMMARY ON RESEARCH OUTCOMES OF THIS PROGRAM

(Please state the followings concisely and clearly)

1. General Description of the Program: Including Objectives of the Program

The research attempts to offer econometric explanations to the near random-walk exchange rates. It argues that previous empirical evidence for or against predictability in exchange rate movements might have been considerably flawed by the existence of estimation risk due to the strong persistence in fundamentals. The primary goal of the project is in a pursuit of a more reliable inference procedure for the predictability both in-sample and out-of-sample by appropriately controlling the estimation risk.

To achieve the goal, an averaging estimator that combines information optimally both from the univariate time series under study and from cross-sectional time series is developed.

Another goal of the project for the current year is to explore another form of averaging, particularly in the time series context. This is important because for the studies using time series where the data under consideration typically do not have a long span, and the regressions are featured by the presence of serial correlated errors of unknown forms. We propose another simple averaging estimatior that is able to attain efficency gains without the knowledge of autocorrelation in errors.

Breakthroughs and Major Achievements

Evidence for the exchange rate predictability in the past literature has been mixed. In contrast, the current project, after controlling the estimation risks, is able to establish a more uniform evidence for the predictability, whether the forecasting horizons are short or long. This is somehow remarkable because to our knowledge, little evidence for the exchange rate predictability in the short horizons was found in the literature.

In addition to establishing evidence for the predictability, two major conclusions emerging from part of the research so far can be summarized: 1) the magnitude of the estimation risks is so high that the exchange rate predictability can be masked even when it exists in the data; 2) The information about exchange rate movements from cross-section is valuable in the ways that it can reduce the estimation risk and thus improve the testing power for predictability, if it could be exploited effectively as the averaging estimator does.

The new averaging estimator proposed from the research this year possesses the optimality in the sense that the associated mean squared errors (MSE) are found to be no more than the Gauss-Markov bound asymptotically, regardless of the degrees of error dependence. Not only this, to implement the proposed averaging estimator can not be simpler than adding ordinary least squared estimator (OLS hereafter) and first-differencing estimator (FD in brief) together with respective weights that are determined optimally.

2. Categorized Summary of Research Outcomes. The criteria for top conferences and journals should be given and introduced briefly in the beginning of this section. In each research area, please give a brief summary on the research outcomes associated with the area. Note that the summaries should be consistent with the statistics given in Form3. Please list and number each research outcomes in sorted order in Appendix II, and list all the publications in top conferences and journals in Appendix III.

2.1 The development of an avaraging estimator that combines cross-sectional information :

An averaging estimator that is to control potential estimation risks associated with the predictive regression

is developed in the first-year study. The sources of the estimation risks comes from high persistence of predictive regressors, and the dependent variable being the overlapping sums of short-horizon change in log exchange rate. The former creates bias in small-samples and the latter brings forth remarkable estimation variability in long-horizon predictions.

The considered averaging estimator optimally combines two alternative estimators that differ in their bias and precision characteristics. By construction, the suggested estimator for the slope coefficients utilizes information from cross-sections in a similar way that the panel-based estimators do. The implicit assumption underlying the use of information from cross-sections for our estimator, however, is very much different from that for the panel-based estimators. In contrast, the panel-based estimators are built on the assumption that the slope coefficients are all the same for all the cross-sectional countries. On the other hand, the averaging estimator allows for separate slope estimate for each cross-section country as the OLS estimator does, but makes use of the cross-sectional information that the OLS estimator does not. Thus both the averaging estimator and the pooled estimator are the same to reduce the estimation errors, but differ in the way how the cross-sectional information is processed. Yet, our averaging estimator has the advantages of producing more reasonable slope estimates.

2.2 Risk reduction: simulation analysis

We examined to what extent the proposed estimator can improve over the traditional estimator in terms of risk reduction through simulations. Under the setup that mimics the reality, we documented that the averaging estimator empirically dominates the least-square (LS) estimator, regardless of which simulation scenario is considered. Virtually the risk reductions using the averaging estimator can be as large as between 10\% and 35\%, compared with the LS estimator. More importantly, the risk improvement by the averaging estimator is embodied further into power gains in testing. Our simulation shows that the power gains from using the averaging estimator, again relative to the LS estimator, is 10% to 30% or more in many cases. An significant implication of the finding is simply that the predictability alternative can now be better detected from the data when the test statistics are based on the averaging estimator.

2.3 A re-examination of the exchange rate predictability

We re-investigated the empirical validity of the exchange rate predictability applying the averaging estimator. The testing strategy basically follows that utilized in the literature where these studies all base their inference on the bootstrap approach in order to control for small-sample bias for which the asymptotic approximation generally fails to correct.

We accessed the relative forecast accuracy of the two competing models with Theil's U and DM statistics. It should be noted that the problem with estimating the long-run variance precisely when calculating the DM statistic often leads to spurious inference. Important messages emerging from the empirical exercises include:

1) There is now much more significant evidence presented for the dominance of the monetary model over the random walk when predicting, after accounting for estimation risks using the considered estimator. With only few exceptions, the p-values associated with the averaging estimator for both statistics are smaller, relative to those associated with the LS estimator.

2) It stands out from the results that controlling over the risks uncovers more favorable evidence in supports of the monetary model, while there is essentially no evidence for so when leaving the risks unattended. Many more instances of this are found from the reported Theil’s U statistic. Particularly, at almost all horizons, the monetary model is found to be superior to the random walk in terms of predictability for Germany and Japan. This contrasts sharply with the previous findings where little evidence for predictability is reported. Considering the Theil's U statistic is more robust, this evidence lends quite a good deal of credence to the predictability at both short- and long-horizons.

2.4 Asymptotic theory for the averaging estimator combining cross-sectional information

The use of the averaging estimator in testing for exchange rate predictability brings forth some econometric

interesting questions. This entails the development of an asymptotic theory of the averaging estimator. We invoke a local-to-unity framework to build the asymptotic theory based on the observation with inherent high persistence in the data. We are now able to derive the asymptotic distributions of the averaging estimator under the simplified assumptions where regression errors are uncorrelated with predicting variables. The asymptotic distribution derived is a mixture normal. The mixture normal collapses into the limit distribution of the least-square estimator, or that of the panel estimator, when either receives zero weights in forming the averaging estimator.

2.5 The development of a new averaging estimator in the time series context

The new averaging estimator to attain more efficiency gains than the Gauss-Markov bound is formed by combining OLS with FD. Indeed each of the aforementioned estimators provides some particular information regarding the regression parameters of concern for the cases where it works well. OLS performs more satisfactorily when the autocorrelation in errors is mild, while FD goes another direction. Since the degree of autocorrelation in errors is unknown, determining which estimator to adopt amounts to a bet on two extremes. However, our averaging estimator is obtained by optimally combining the two specific estimators, and is found to have smaller estimation risks than either of the two estimators that is to combined. Specifically, the averaging estimator is obtained by associating both OLS and FD with respective weights. The weights are however determined such that the asymptotic MSE for the averaging estimator is minimized. It should be emphasized that while consisting of both the estimators that are linear by construction, the averaging estimator is nevertheless non-linear. Intuitively it is such the non-linearity nature that the proposed averaging estimator can gain more efficiency than the Gauss-Markov bound, defined for the family of linear estimators. Further, our simulation results show that the averaging estimator is much preferred when information about the degrees of persistence in regression errors is unknown. The numerical evidence concurs on the theoretical predictions of the estimator.

3. Program Management: the Mechanism for Promoting Collaboration and Integration among the Institutes Involved

The mini conference held at Academia Sinica in Jan 2007, and Feb 2008 exposed me to the ideas contributed by other principle investigators of different sub-projects. Admittedly I learned quite a bit from these team partners. Some of the work and results were intriguing. Importantly, I found that there should have more links to each other among sub-projects than it used to project.

The study on the averaging estimator in time series context was presented at the third mini conference in August 2008, Academia Sinica. While the research is the only study that falls into the category of econometrtic theory, a few important observations and comments regarding the idea of the averaging estimator were made by conference participants, probably because of its intuitive appealing. These observations and comments turn out to be the focal points for future research for the year to come. It will be detailed somehow in the following section.

4. A Summary of the Post-Program Plan（Including the Detailed Description of Budget and Plan Adjustment of the next year）

There are two potential directions that can be after for future research. The first is to apply the averaging notion to panel data where the estimation suffers bias and inefficiency due to, again, short span of realizations in time horizons, as in typical time series. The lack of efficiency in estimations for typical panel data is well known. Worse is the bias problem when dynamic panel data is under study. With lag dependent variables as explanatory regressors, the autoregressive coefficients have been long known to be biased downwards, as in the conventional auto-regressions. While the averaging may well be applied to the panel context for the purposes of efficiency

gains and bias reductions, work along the line will prove to be very challenging and time-demanding, due to the the complications arising from the dimensionality of the panel data.

Another important work is to explore the possible link of the averaging estimators to the family of the GMM estimator. This is a very reasonable and interesting inquiry because the averaging estimator is in fact made up of the two estimators, OLS and FD, which can be obtained by method of moments, individually. Therefore, the averaging estimator in essence should share some common characteristics with the GMM estimator. The GMM estimators arise in the over-identification cases where number of the moment conditions exceeds that of the parameters to be estimated. Information from various moments is thus combined with the use of an appropriate weighting matrix where the respective contribution from each moment is taken into account. The respective weight associated with OLS and FD in the averaging estimator proposed depends on the contribution of each combined estimator. The two estimators differ from each other by their objective functions. The GMM estimators are developed to minimize the squared difference between the true moments and the estimated ones, while the averaging estimator is obtained when the associated mean squared error is minimized. It proves worthwhile to examine how the two types of the estimators differ in terms of their statistical properties. Of the properties of major interest is to investigate whether the weighting schemes in the averaging estimator could help understand and thus improve the poor small sample performance of the GMM estimators due to ill calculations of the corresponding weighting matrix. This subtlety will be one of important focal points for future research.

5. International Cooperation Activities (Optional)

Prof. Bruce Hansen of University of Wisconsin at Madison has been working on the averaging estimator around the same time as the research got started. One of his first papers along the line got published in a recent issue of Econometrica and Journal of Econometrics, marking research on the averaging estimator a potential important direction to move in the future. Possible research collaborations with him in terms of visiting him would greatly help improve the exposition of my research.

VI. APPENDIX I: MINUTES FROM PROGRAM DISCUSSION MEETINGS

VII. APPENDIX II:

1. **PUBLICATION LIST（CONFERENCES, JOURNALS, BOOKS, BOOK CHAPTERS, etc.）**

   DOING JUSTICE TO FUNDAMENTALS IN EXCHANGE RATE FORECASTING: A CONTROL OVER ESTIMATION RISKS, PRESENTED IN NORTH AMERICAN SUMMER MEETING OF ECONOMETRIC SOCIETY, JUNE 2007, DUKE UNIVERSITY, USA; AND EUROPEAN SUMMER MEETING OF ECONOMETRIC SOCIETY, AUGUST 2007, BUDAPEST, HUNGARY.

2. **PATENT LIST**
3. **INVENTION LIST**
4. **LIST OF WORKSHOPS/CONFERENCES HOSTED BY THE PROGRAM**
5. **LIST OF PERSONAL ACHIEVEMENTS OF THE PIS**
6. **LIST OF TECHNOLOGY TRANSFERS**
7. **LIST OF TECHNOLOGY SERVICES**

VIII. Appendix III: List of Publications in "Top" Journals and Conferences

IX. APPENDIX IV: SLIDES ON SCIENCE AND TECHNOLOGY BREAKTHROUGHS

(TWO SLIDES FOR EACH BREAKTHROUGH)

Program for Promoting Academic Excellence of Universities（Phase II）

Midterm ASSESSMENT

PROGRAM/Sub-project TITLE: AVERAGING TO IMPROVE EFFICIENCY IN TIME SERIES CONTEXT

	ASSESSMENT SUBJECT	SCORE （1~5, LOW TO HIGH）
PROGRAM'S CONTENTS & PERFORMANCE	Importance & Innovation of the Program's Major Tasks	4
	Clarity and Presentation of the Report	3
	Viability of the Program's Approaches & Methodologies	4
	Principal Investigator's Competence for Leading the Program	4
	Interface & Integration between Overall & Sub-Project(s)	3
	Interface & Integration among All Sub-Projects	3
	Manpower & Expenditures	4
PROGRAM'S RESULTS	Contribution in Enhancing the Institute's International Academic Standing	4
	Impact on Advancing Teaching or on Technology Development	4
Total Score		33

REVIEWER'S COMMENTS & SUGGESTION:

PRINCIPLE INVESTIGATOR'S FEEDBACK: (AVAILABLE)

Program Reviewer's Signature:____

Notes: The program reviewers are invited by the National Science Council.

Averaging to Improve Efficiency in Time Series Regressions

February 17, 2009

Abstract

This paper proposes a simple averaging estimator to increase the efficiency of the regression coefficient estimates, relative to the usual ordinary least squares (OLS), estimator when the error term having nonparametric autocorrelation.

Key words: averaging estimator; time series regression

1 Introduction

Consider the regression model consisting of stationary time series processes as follows:

$$C_t = \gamma + Z_t^\top \beta + \varepsilon_t, \quad t = 1, 2, \ldots, n, \tag{1}$$

where γ represents a scalar finite constant, Z_t is a $(K \times 1)$ random vector whose j-th element is $Z_{t,j}$, and β is a $(K \times 1)$ non-stochastic vector of unknown regression coefficients to be estimated and tested. Adaptive estimation method based on an approximate frequency-domain generalized least squares (GLS) has been considered by Hannan (1963) for the model in (1) when ε_t is a short memory process with nonparametric autocorrelation. The methodology of Hannan (1963) has been extended by Hannan (1965), Hannan and Terrell (1972, 1973), and Robinson (1976) to other interesting econometric models. Robinson and Hidalgo (1997) and Hidalgo and Robinson (2002) further apply the frequency-domain method of Hannan (1963) to the cases where ε_t and Z_t can be long memory processes.

The most well-known time-domain method for the model in (1) surely is the usual ordinary least squares (OLS) estimator. The OLS estimator basically cannot achieve Gauss-Markov bound when ε is not an independently identically distributed (i.i.d.) process. Thus, GLS-type method has been proposed to increase the efficiency of the regression coefficient estimate when ε_t admits a specific parametric form. For example, the Cochrane and Orcutt (1949) estimator requires ε_t as an autoregressive process of order 1, or AR(1). Some authors, including Maeshiro (1976), Chipman (1979), and Krämer (1982) and references therein, suggest that the first-differenced (FD) estimator can be an approximation to the GLS estimator when estimating the coefficient of the linear trend. When ε_t having nonparametric autocorrelation, however, we do not have a clear understanding about the relative performance of the OLS and FD estimators in estimating β. In this paper we thus fill the gap of literature by suggesting a time-domain semiparametric Stein-like (SPSL) estimator advocated in Judge and Mittelhammer (2004) to increase the efficiency of the regression coefficient estimate relative to both the OLS and FD estimators for the model in (1) where Z_t and ε_t are stationary processes admitting nonparametric autorrelation.

The proposed SPSL estimator is a linear combination of the OLS and the FD estimator. The SPSL estimator is risk superior to the OLS and FD estimator in MSE under suitable regularity conditions outlined in Judge and Mittelhammer (2004). The simulations reveal that the finite sample power performance of the proposed shrinkage estimator are 99% more powerful than that of OLS and FD estimator, respectively, when the sample is 100?. When sample size increase, the percentages become ?.

2 Main statistics

With a sample of size n and define $\overline{S}_{T_1:T_2}$ as the sample mean of the random variable S_t from $t = T_1$ to $t = T_2$, the usual OLS estimator for the model in (1) is:

$$\widehat{\beta}_{n,\text{OLS}} = \left[\sum_{t=1}^{n}(Z_t - \overline{Z}_{1:n})Z_t^\top\right]^{-1} \sum_{t=1}^{n}\left(Z_t - \overline{Z}_{1:n}\right) C_t. \tag{2}$$

Define $\triangle = 1 - L$, where L is the usual lag operator ($Lx_t = x_{t-1}$), the FD estimator for the model in (1) is computed as:

$$\widehat{\beta}_{n,\text{FD}} = \left[\sum_{t=2}^{n}\left(\triangle Z_t - \overline{\triangle Z}_{2:n}\right)\triangle Z_t^\top\right]^{-1} \sum_{t=2}^{n}\left(\triangle Z_t - \overline{\triangle Z}_{2:n}\right)\triangle C_t. \tag{3}$$

We compute the shrinkage estimator as follows:

$$\widehat{\beta} = \widehat{w}\,\widehat{\beta}_{2:n,\text{OLS}} + (1 - \widehat{w})\widehat{\beta}_{n,\text{FD}}, \tag{4}$$

where

$$\widehat{\beta}_{2:n,\text{OLS}} = \left[\sum_{t=2}^{n}(Z_t - \overline{Z}_{2:n})Z_t^\top\right]^{-1} \sum_{t=2}^{n}\left(Z_t - \overline{Z}_{2:n}\right) C_t, \tag{5}$$

and $\widehat{w}$ is the weight estimated from the data. The choice of observations used for estimation is to ensure that the sample sizes used for the OLS and FD estimators are compatible. The theoretical foundation of calculating $\widehat{w}$ will be discussed later.

Similar to the arguments in Judge and Mittelhammer (2004, p. 480), the proposed SPSL estimator, $\widehat{\beta}$, can reduce the estimation risks for the time series regression model in (1), because it has a smaller expected quadratic risk than the OLS estimator. Following Judge and MIttelhammer (2004), we note that, whenever the OLS and FD estimators are not perfectly correlated, the optimal weighted linear combination estimator $\widehat{\beta}$ in (4) will, under quadratic loss, be superior to the OLS estimator. The estimator $\widehat{\beta}$ is in the general form of the Stein rule family of estimators, where shrinkage of the base estimator, OLS, is toward the alterative estimator, FD. The estimator is drawn toward the alternative estimator when the variance of the OLS estimator is higher, and drawn toward the OLS estimator when the

FD estimator has a higher variance. The combined-models formulation is similar in spirit to the Bayesian model-averaging method of Hoeting, et al. (1999, 2002). The difference is that the Bayesian model-average methods are not optimized with respect to any particular loss function.

We now discuss the asymptotic properties of the shrinkage estimator. Note that

$$\begin{bmatrix} \widehat{\beta}_{2:n,\mathrm{OLS}} \\ \widehat{\beta}_{n,\mathrm{FD}} \end{bmatrix} = \widehat{Q}_n \begin{bmatrix} n^{-1} \sum_{t=2}^{n} \left(Z_t - \overline{Z}_{2:n} \right) C_t \\ n^{-1} \sum_{t=2}^{n} \left(\triangle Z_t - \overline{\triangle Z}_{2:n} \right) \triangle C_t \end{bmatrix}, \tag{6}$$

where

$$\widehat{Q}_n = \begin{bmatrix} \left[n^{-1} \sum_{t=2}^{n} (Z_t - \overline{Z}_{2:n}) Z_t^\top \right]^{-1} & 0 \\ 0 & \left[n^{-1} \sum_{t=2}^{n} \left(\triangle Z_t - \overline{\triangle Z}_{2:n} \right) \triangle Z_t^\top \right]^{-1} \end{bmatrix}. \tag{7}$$

It follows that

$$\begin{bmatrix} n^{1/2}(\widehat{\beta}_{2:n,\mathrm{OLS}} - \beta) \\ n^{1/2}(\widehat{\beta}_{n,\mathrm{FD}} - \beta) \end{bmatrix} = \widehat{Q}_n \begin{bmatrix} n^{-1/2} \sum_{t=2}^{n} \left(Z_t - \overline{Z}_{2:n} \right) \varepsilon_t \\ n^{-1/2} \sum_{t=2}^{n} \left(\triangle Z_t - \overline{\triangle Z}_{2:n} \right) \triangle \varepsilon_t \end{bmatrix} = \widehat{Q}_n \widehat{Y}_n. \tag{8}$$

We observe that

$$\widehat{Q}_n - Q \xrightarrow{p} 0, \tag{9}$$

where Q in (9) is $O(1)$ and uniformly positive definite under suitable regularity conditions.

Under suitable regularity conditions, we can show that $\widehat{Y}_n$ in (8) is asymptotically distributed as:

$$\widehat{Y}_n \Rightarrow N \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} V_{11} & V_{12} \\ V_{12}^\top & V_{22} \end{bmatrix} \right), \tag{10}$$

where $\Rightarrow$ stands for weak convergence. It follows that we have

$$\begin{bmatrix} n^{1/2}(\widehat{\beta}_{2:n,\mathrm{OLS}} - \beta) \\ n^{1/2}(\widehat{\beta}_{n,\mathrm{FD}} - \beta) \end{bmatrix} \Rightarrow N \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} V_{\mathrm{OLS}} & \Sigma \\ \Sigma^\top & V_{\mathrm{FD}} \end{bmatrix} \right). \tag{11}$$

Combining the results in (11) and (2.5) of Judge and Mittelhammer (2004), we compute the weighting constant as:

$$w = 1 - \frac{\mathrm{tr}(V_{\mathrm{OLS}}) - \mathrm{tr}(\Sigma)}{\mathrm{tr}(V_{\mathrm{OLS}}) + \mathrm{tr}(V_{\mathrm{FD}}) - 2\,\mathrm{tr}(\Sigma)}. \tag{12}$$

$\widehat{w}$ is calculated based on the results in (12). As a consequence, the shrinkage estimator $\widehat{\beta}$ is asymptotically distributed as:

$$n^{1/2}(\widehat{\beta} - \beta) \Rightarrow N \left(0, w^2 V_{\mathrm{OLS}} + (1-w)^2 V_{\mathrm{FD}} + w(1-w)(\Sigma + \Sigma^\top) \right). \tag{13}$$

The results in (13) can be used to construct a t-ratio statistic for testing the value of β in (1) based on the asymptotic properties of the shrinkage estimator $\widehat{\beta}$ in (13).

3 Monte Carlo experiment

This section focuses on the finite sample performance of the shrinkage estimator $\widehat{\beta}$ as compared to the OLS and FD counterparts for the regression model with stationary regressor and errors. Without loss of generality, only one regressor is considered in the experiment, i.e., we assume $K = 1$ throughout this section. Moreover, $\gamma = 0$ is assumed throughout this section.

We focus on the cases where ε_t and Z_t are both generated as AR(1) processes:

$$(1 - \phi_\varepsilon L)\varepsilon_t = v_t, \qquad (1 - \phi_Z L)Z_t = w_t, \tag{14}$$

such that v_t and w_t both are zero-mean normally i.i.d. white noise processes with:

$$E(v_t^2) = \sigma_v^2, \qquad E(w_t^2) = \sigma_w^2. \tag{15}$$

The value of σ_v^2 and σ_w^2 in (41) are chosen to ensure the variance of ε_t and Z_t are both equal to 1. The values of ϕ_ε and ϕ_Z ranges from 0.1 to 0.9.

In the context of stochastic regressor framework, we generate 5,000 replciation of Z_t and ε_t based on the following model:

$$C_t^l = \beta_1 Z_t^l + \varepsilon_t^l, \quad t = 1, 2, \ldots, n, \quad l = 1, 2, \ldots, 5000, \tag{16}$$

where l denotes the l-th replication of the data. β_1 can be 1 or 0.9 for investigating the empirical powers of the shrinkage estimator given that the null hypothesis for β_1 is always tested as:

$$H_0 : \beta_1 = \beta_0 = 1. \tag{17}$$

We adopt the the long-run variance estimator of Robinson (1998) to implement the shrinkage estimator and conduct inference for the OLS, FD, and shrinkage estimators, because it does not involve the difficult choices of kernel function, bandwidth parameter, or lag length of AR model typically used in the literature. Particularly, V_{11} in (10) can be estimated with $\widehat{V}_{11}$:

$$\widehat{V}_{11} = \sum_{i=-(n-1)+1}^{(n-1)-1} \left(\widehat{c}_{i,\mathrm{OLS}} \times \widehat{d}_{i,\mathrm{OLS}} \right), \tag{18}$$

where

$$\widehat{c}_{i,\mathrm{OLS}} = (n-1)^{-1} \sum_{2\leq t,t+i\leq n} e_t\, e_{t+i}, \qquad \widehat{d}_{i,\mathrm{OLS}} = (n-1)^{-1} \sum_{2\leq t,t+i\leq n} (Z_t - \overline{Z}_{2:n})(Z_{t+i} - \overline{Z}_{2:n})^\top, \tag{19}$$

and e_t are the residuals from the OLS estimation:

$$C_t - \overline{C}_{2:n} = (Z_t - \overline{Z}_{2:n})^\top \widehat{\beta}_{2:n,\mathrm{OLS}} + e_t, \qquad t = 2, 3, \ldots, n. \tag{20}$$

Similarly, V_{22} can be estimated with $\widehat{V}_{22}$:

$$\widehat{V}_{22} = \sum_{i=-(n-1)+1}^{(n-1)-1} \left(\widehat{c}_{i,\mathrm{FD}} \times \widehat{d}_{i,\mathrm{FD}}\right), \tag{21}$$

where

$$\begin{cases} \widehat{c}_{i,\mathrm{FD}} = (n-1)^{-1} \sum_{2\leq t,t+i\leq n} e_{t,\mathrm{FD}}\, e_{t+i,\mathrm{FD}}, \\ \widehat{d}_{i,\mathrm{FD}} = (n-1)^{-1} \sum_{2\leq t,t+i\leq n} (\triangle Z_t - \overline{\triangle Z}_{2:n})(\triangle Z_{t+i} - \overline{\triangle Z}_{2:n})^\top, \end{cases} \tag{22}$$

and $e_{t,\mathrm{FD}}$ are the residuals from the FD estimation:

$$\triangle C_t - \overline{\triangle C}_{2:n} = \left(\triangle Z_t - \overline{\triangle Z}_{2:n}\right)^\top \widehat{\beta}_{n,\mathrm{FD}} + e_{t,\mathrm{FD}}, \quad t = 2, 3, \ldots, n. \tag{23}$$

In a similar vein, V_{12} in (10) can be estimated with $\widehat{V}_{12}$:

$$\widehat{V}_{12} = \sum_{i=-(n-1)+1}^{(n-1)-1} \left(\widehat{c}_i \times \widehat{d}_i\right), \tag{24}$$

such that

$$\begin{cases} \widehat{c}_i = (n-1)^{-1} \sum_{2\leq t,t+i\leq n} e_t\, e_{t+i,\mathrm{FD}}, \\ \widehat{d}_i = (n-1)^{-1} \sum_{2\leq t,t+i\leq n} (Z_t - \overline{Z}_{2:n})(\triangle Z_{t+i} - \overline{\triangle Z}_{2:n})^\top, \end{cases} \tag{25}$$

Table 1 contain the RMSE of the OLS, FD, and shrinkage estimators in estimating the regression coefficient β. The results shows that, for a given value of ϕ_Z, the performance of the OLS estimator deteriorates with the increasing value of ϕ_ε. This is what we expect because we note that the OLS estimator achieve the Gauss-Markov bound when the error term is a Gaussian white noise. On the other hand, the efficiency of the FD estimator improves with the increasing value of ϕ_ε. This corresponds to the findings in Chipman (1979) and Krämer (1982) that the FD estimator is an approximation to the generalized least squares (GLS) estimator when estimating the coefficient of the linear trend.

For ease of comparison, we define RMSE_ξ as the RMSE of the estimator ξ in estimating β of the model in (6), and compare the finite sample relative efficiency of OLS estimator to its shrinkage counterpart as:

$$\text{relative efficiency of OLS to shrinkage estimator in estimating } \beta = \frac{\text{RMSE}_{\text{OLS}}}{\text{RMSE}_{\widehat{\beta}}}. \tag{26}$$

The shrinkage estimator is more efficient than the OLS counterpart in estimating β if we find the ratio in (16) is greater than 1.

Table 2 shows that the shrinkage estimator performs much better than the OLS estimator for the 81 cases considered in Table 2, especially when ϕ_ε is larger. Indeed, we only find 10 out of 81 cases where the OLS can beat the shrinkage estimators when $T = 100$. Even within these 10 cases, the relative efficiency of the OLS estimator as compared to the shrinkage estimator are very much close to each other, because the ratio are very close to 1. Moreover, we also find the relative performance of shrinkage estimator as compared to the OLS ones improves when the sample increases. For example, we now observe 9 out of 81 cases that the OLS estimator can beat the shrinkage estimator when $n = 200$. Moreover, there are only 3 cases that the shrinkage estimator is inferior to the OLS estimator as the sample size increases to be 400, and the ratios from these 3 cases are very close to 1.

Table 3 shows that the shrinkage estimator also performs much better than the FD estimator when ϕ_ε is not close to the boundary of 0.9. Indeed, we only find 18 out of 81 cases where the FD can beat the shrinkage estimators when $T = 100$. Even within these 18 cases, the relative efficiency of the OLS estimator as compared to the shrinkage estimator are very much close to each other. Again, we find the relative performance of shrinkage estimator as compared to the OLS counterpart improves with an increasing sample size. For example, we observe only 10 out of 81 cases that the FD estimator outperform the shrinkage one when $T = 200$, the ratio are more close to 1 as compared to the case $T = 100$.

4 Conclusion

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Table 1. RMSE from Estimating the Regression Coefficient β: $n = 100$

		ϕ_Z								
ϕ_ε	Estimator	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.1	OLS	0.104	0.104	0.106	0.105	0.108	0.111	0.114	0.118	0.129
	FD	0.122	0.128	0.132	0.139	0.152	0.166	0.191	0.229	0.312
	$\widehat{\beta}$	0.105	0.105	0.107	0.105	0.109	0.113	0.116	0.120	0.131
0.2	OLS	0.103	0.108	0.108	0.112	0.112	0.115	0.120	0.129	0.144
	FD	0.112	0.119	0.124	0.130	0.140	0.158	0.178	0.213	0.299
	$\widehat{\beta}$	0.101	0.105	0.106	0.109	0.111	0.115	0.119	0.128	0.146
0.3	OLS	0.105	0.107	0.111	0.114	0.119	0.123	0.130	0.137	0.154
	FD	0.102	0.109	0.113	0.121	0.131	0.145	0.164	0.197	0.274
	$\widehat{\beta}$	0.097	0.099	0.102	0.107	0.112	0.117	0.125	0.134	0.151
0.4	OLS	0.107	0.109	0.115	0.120	0.123	0.130	0.138	0.148	0.167
	FD	0.095	0.098	0.104	0.114	0.120	0.135	0.154	0.183	0.253
	$\widehat{\beta}$	0.092	0.094	0.099	0.105	0.109	0.116	0.126	0.138	0.160
0.5	OLS	0.107	0.111	0.116	0.121	0.128	0.139	0.146	0.160	0.179
	FD	0.084	0.089	0.094	0.099	0.109	0.120	0.137	0.166	0.234
	$\widehat{\beta}$	0.083	0.087	0.091	0.095	0.103	0.111	0.121	0.138	0.165
0.6	OLS	0.105	0.112	0.119	0.127	0.135	0.146	0.160	0.177	0.202
	FD	0.074	0.078	0.083	0.090	0.096	0.108	0.123	0.147	0.208
	$\widehat{\beta}$	0.073	0.077	0.081	0.088	0.094	0.104	0.117	0.134	0.169
0.7	OLS	0.106	0.112	0.120	0.133	0.141	0.154	0.169	0.189	0.230
	FD	0.062	0.066	0.071	0.077	0.083	0.091	0.104	0.128	0.178
	$\widehat{\beta}$	0.062	0.065	0.071	0.077	0.082	0.090	0.103	0.123	0.163
0.8	OLS	0.105	0.114	0.125	0.132	0.152	0.164	0.184	0.213	0.261
	FD	0.050	0.053	0.058	0.061	0.067	0.073	0.086	0.104	0.147
	$\widehat{\beta}$	0.050	0.053	0.058	0.061	0.067	0.074	0.086	0.105	0.148
0.9	OLS	0.103	0.112	0.121	0.135	0.150	0.166	0.191	0.228	0.292
	FD	0.035	0.037	0.039	0.042	0.045	0.052	0.061	0.072	0.103
	$\widehat{\beta}$	0.035	0.037	0.039	0.042	0.046	0.053	0.061	0.074	0.109

Notes: All the results are based on 5,000 replications of the simulated data defined in (14), (15), (16), and $\beta_1 = 1$. $\widehat{\beta}$ is the shrinkage estimator defined in (4).

Table 2. Relative Efficiency of OLS Estimator to the Shrinkage Counterpart from Estimating the Regression Coefficient β

	ϕ_Z								
ϕ_ε	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
					$n = 100$				
0.1	0.9927	0.9883	0.9927	0.9951	0.9875	0.9850	0.9883	0.9806	0.9853
0.2	1.0225	1.0225	1.0183	1.0201	1.0115	1.0031	1.0011	1.0034	0.9896
0.3	1.0851	1.0784	1.0812	1.0651	1.0592	1.0530	1.0428	1.0258	1.0200
0.4	1.1600	1.1549	1.1638	1.1399	1.1323	1.1271	1.0951	1.0754	1.0445
0.5	1.2903	1.2760	1.2732	1.2810	1.2463	1.2536	1.2088	1.1616	1.0894
0.6	1.4337	1.4530	1.4653	1.4416	1.4432	1.4012	1.3669	1.3200	1.1929
0.7	1.7015	1.7163	1.7066	1.7347	1.7184	1.7189	1.6359	1.5386	1.4060
0.8	2.0998	2.1511	2.1567	2.1750	2.2528	2.2238	2.1449	2.0226	1.7683
0.9	2.9363	3.0215	3.1114	3.1987	3.2812	3.1448	3.1218	3.0856	2.6802
					$n = 200$				
0.1	0.9988	0.9964	0.9983	1.0019	0.9965	0.9927	0.9993	0.9944	0.9950
0.2	1.0437	1.0298	1.0283	1.0202	1.0231	1.0200	1.0202	1.0051	0.9990
0.3	1.0900	1.0861	1.0933	1.0746	1.0658	1.0646	1.0515	1.0339	1.0095
0.4	1.1756	1.1680	1.1728	1.1604	1.1461	1.1402	1.1080	1.0811	1.0449
0.5	1.2875	1.2978	1.2954	1.2829	1.2725	1.2300	1.2179	1.1665	1.0916
0.6	1.4653	1.4743	1.4977	1.4716	1.4655	1.4293	1.3958	1.3167	1.2072
0.7	1.6822	1.7379	1.7563	1.7862	1.7523	1.7258	1.6646	1.5688	1.3979
0.8	2.1147	2.2099	2.2650	2.2325	2.2573	2.2542	2.2389	2.1143	1.8576
0.9	3.0284	3.1638	3.2378	3.3515	3.3323	3.3569	3.3152	3.3012	2.9232
					$n = 400$				
0.1	1.0040	1.0039	1.0051	1.0031	1.0016	0.9999	0.9998	1.0009	0.9984
0.2	1.0371	1.0379	1.0329	1.0283	1.0270	1.0247	1.0140	1.0145	1.0015
0.3	1.0905	1.0954	1.0891	1.0824	1.0757	1.0794	1.0557	1.0331	1.0241
0.4	1.1620	1.1803	1.1767	1.1758	1.1650	1.1569	1.1240	1.1032	1.0520
0.5	1.3104	1.3126	1.3058	1.2833	1.2833	1.2558	1.2285	1.1557	1.1012
0.6	1.4536	1.4726	1.4863	1.5035	1.4795	1.4403	1.4123	1.3148	1.2021
0.7	1.7533	1.7560	1.7767	1.7674	1.7785	1.7382	1.6775	1.5760	1.3966
0.8	2.1574	2.2205	2.3092	2.2825	2.2976	2.2803	2.2484	2.0852	1.8654
0.9	3.0666	3.1960	3.2935	3.4127	3.4700	3.5189	3.4484	3.3625	3.0185

Notes: All the results are based on 5,000 replications of the simulated data defined in (14), (15), (16), and $\beta_1 = 1$.

Table 3. Relative Efficiency of FD Estimator to the Shrinkage Counterpart from Estimating the Regression Coefficient β

	ϕ_Z								
ϕ_ε	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
					$n = 100$				
0.1	1.1604	1.2109	1.2357	1.3193	1.3872	1.4704	1.6506	1.9038	2.3840
0.2	1.1093	1.1298	1.1718	1.1904	1.2684	1.3722	1.4948	1.6626	2.0467
0.3	1.0562	1.0946	1.1015	1.1307	1.1749	1.2377	1.3102	1.4724	1.8097
0.4	1.0334	1.0439	1.0538	1.0864	1.1056	1.1694	1.2283	1.3312	1.5780
0.5	1.0119	1.0221	1.0310	1.0470	1.0629	1.0815	1.1299	1.2060	1.4210
0.6	1.0071	1.0067	1.0165	1.0243	1.0267	1.0362	1.0532	1.1012	1.2281
0.7	0.9990	1.0031	1.0063	1.0002	1.0097	1.0127	1.0102	1.0450	1.0899
0.8	0.9984	0.9977	0.9967	0.9993	0.9953	0.9958	1.0014	0.9887	0.9916
0.9	0.9984	0.9962	0.9976	0.9966	0.9920	0.9930	0.9936	0.9791	0.9476
					$n = 200$				
0.1	1.1657	1.2067	1.2718	1.3342	1.4258	1.5191	1.7158	1.9365	2.5396
0.2	1.1080	1.1590	1.1801	1.2145	1.2657	1.3631	1.4989	1.6791	2.2373
0.3	1.0684	1.0911	1.1115	1.1383	1.1982	1.2629	1.3544	1.5557	2.0074
0.4	1.0333	1.0579	1.0618	1.0900	1.1254	1.1583	1.2372	1.3816	1.6644
0.5	1.0182	1.0280	1.0360	1.0568	1.0761	1.1048	1.1557	1.2148	1.4661
0.6	1.0113	1.0124	1.0198	1.0231	1.0330	1.0516	1.0695	1.1328	1.2534
0.7	1.0036	1.0025	1.0063	1.0038	1.0119	1.0266	1.0290	1.0614	1.1265
0.8	1.0010	1.0007	0.9987	1.0024	1.0034	1.0052	0.9989	1.0102	1.0415
0.9	0.9985	1.0003	0.9992	0.9991	0.9970	0.9986	0.9969	0.9992	0.9864
					$n = 400$				
0.1	1.1759	1.1997	1.2670	1.3370	1.4171	1.5464	1.7130	1.9882	2.6262
0.2	1.1208	1.1496	1.1904	1.2567	1.2944	1.3799	1.5254	1.7701	2.3178
0.3	1.0741	1.0928	1.1180	1.1636	1.2055	1.2606	1.3819	1.5705	2.0247
0.4	1.0470	1.0543	1.0703	1.0997	1.1176	1.1679	1.2432	1.4070	1.7281
0.5	1.0217	1.0339	1.0368	1.0606	1.0651	1.1143	1.1525	1.2538	1.4761
0.6	1.0060	1.0130	1.0239	1.0225	1.0340	1.0552	1.0851	1.1608	1.3101
0.7	1.0023	1.0077	1.0115	1.0100	1.0138	1.0231	1.0389	1.0636	1.1613
0.8	1.0018	1.0032	0.9989	1.0052	1.0064	1.0039	1.0158	1.0177	1.0582
0.9	1.0001	0.9999	0.9997	0.9993	1.0002	0.9990	0.9995	1.0016	1.0038

Notes: All the results are based on 5,000 replications of the simulated data defined in (14), (15), (16), and $\beta_1 = 1$.

Table 4. Rejection Percentages of the Shrinkage Estimator under the Null

		ϕ_Z								
ϕ_ε	n	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.1	100	7.02	6.88	6.96	6.44	6.96	7.44	8.00	8.04	10.66
	200	6.12	6.02	5.70	6.02	5.88	6.36	6.32	6.82	8.24
	400	5.14	6.04	5.54	5.40	5.66	5.88	5.86	6.22	7.34
0.2	100	6.60	7.26	6.60	6.46	7.06	7.10	7.70	8.66	11.24
	200	5.60	5.44	5.88	6.22	6.66	6.18	6.88	6.68	7.94
	400	5.32	5.58	5.26	5.32	5.96	5.24	6.02	6.28	6.98
0.3	100	6.86	6.38	6.38	6.60	7.06	7.28	7.96	8.48	9.80
	200	5.98	5.40	5.54	6.10	5.84	6.26	6.66	7.12	7.84
	400	5.10	5.16	5.28	5.08	4.94	5.54	5.64	6.20	7.00
0.4	100	7.08	6.50	6.60	6.62	6.58	6.78	8.06	9.00	11.06
	200	5.82	6.10	6.08	5.54	5.76	6.38	6.22	6.90	8.16
	400	5.22	5.02	5.22	5.22	5.28	5.32	5.76	5.80	6.48
0.5	100	6.38	6.20	6.74	6.02	7.04	6.76	7.48	8.26	10.48
	200	5.84	5.88	5.74	5.60	5.40	6.28	5.92	7.04	8.36
	400	4.82	4.66	5.58	5.14	5.58	5.40	6.06	6.18	6.56
0.6	100	5.58	6.30	6.32	6.50	6.40	6.76	7.78	8.38	10.48
	200	5.24	5.34	5.52	5.56	5.62	5.60	6.18	6.84	8.62
	400	5.82	5.26	5.32	5.08	5.16	5.56	4.98	5.78	6.74
0.7	100	6.02	5.54	5.88	6.82	5.84	5.88	6.78	7.80	10.30
	200	5.60	5.66	5.78	5.94	5.80	5.30	6.32	6.66	8.20
	400	5.00	5.12	5.08	5.72	5.32	5.74	5.80	5.78	5.98
0.8	100	6.20	6.00	6.52	5.94	6.10	5.88	6.16	7.36	9.78
	200	5.58	5.12	5.36	5.84	5.78	5.16	5.72	5.44	6.78
	400	5.36	5.38	5.12	5.26	5.48	5.42	5.24	5.86	5.84
0.9	100	5.78	5.76	5.76	5.62	5.60	6.32	6.84	6.64	8.68
	200	5.84	5.50	5.86	5.80	5.94	5.64	5.92	5.86	6.48
	400	5.42	5.36	5.30	5.32	4.88	5.16	5.44	4.88	5.66

Notes: All the results are based on 5,000 replications of the simulated data defined in (14), (15), (16), and $\beta_1 = 1$. $\widehat{\beta}$ is the shrinkage estimator defined in (4).

Table 5. Rejection Percentages of the OLS Estimator under the Null

		ϕ_Z								
ϕ_ε	n	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.1	100	6.48	5.84	6.26	5.52	6.44	6.42	7.14	7.38	9.96
	200	5.46	5.50	5.34	5.70	5.88	5.92	6.18	6.46	7.88
	400	5.08	5.68	5.18	5.24	5.72	5.78	5.70	6.08	7.34
0.2	100	5.64	6.34	6.04	6.32	6.40	6.62	7.34	8.32	10.46
	200	5.64	5.04	5.66	5.86	6.28	5.88	6.70	6.68	7.76
	400	5.02	5.32	4.74	4.96	6.12	5.22	5.52	6.12	6.80
0.3	100	6.12	5.82	6.24	6.04	6.86	6.94	7.66	8.32	9.76
	200	5.88	5.22	5.32	5.78	5.90	6.04	6.50	7.10	7.48
	400	5.22	5.12	5.02	5.24	5.06	5.88	5.36	5.86	6.74
0.4	100	6.86	5.76	6.52	6.42	6.52	6.72	7.58	8.94	11.24
	200	5.84	5.66	6.42	5.50	5.72	6.70	6.32	6.90	8.20
	400	4.50	5.04	5.30	4.78	5.52	5.56	5.62	5.88	6.68
0.5	100	6.44	6.10	5.96	6.18	6.46	7.02	7.78	8.76	10.24
	200	5.82	5.96	5.52	5.42	5.40	6.24	6.26	7.38	8.56
	400	5.56	4.88	5.68	5.46	5.52	5.48	6.50	6.28	6.76
0.6	100	5.28	5.84	6.66	6.38	6.72	7.82	8.80	9.46	10.98
	200	5.40	5.56	5.76	5.76	6.36	5.56	6.86	7.04	8.78
	400	5.36	5.74	4.94	5.60	5.70	5.60	5.74	5.64	7.24
0.7	100	5.82	5.60	5.96	7.48	7.04	7.58	8.08	9.30	12.00
	200	5.32	5.36	5.52	6.66	6.36	5.92	7.32	7.42	9.84
	400	5.42	5.40	5.46	5.54	5.32	5.72	5.84	6.22	6.86
0.8	100	5.86	5.10	6.74	6.18	7.56	7.60	8.40	10.60	13.78
	200	5.30	5.76	5.38	6.00	5.90	6.36	7.32	7.96	10.04
	400	5.12	5.38	5.78	4.82	5.42	6.12	5.48	6.90	7.02
0.9	100	5.20	5.62	5.68	6.96	7.26	7.38	8.80	11.00	14.90
	200	4.78	5.08	5.58	5.78	5.90	6.48	6.94	8.32	10.86
	400	4.70	5.16	5.34	5.28	4.96	5.90	6.04	6.50	8.22

Notes: All the results are based on 5,000 replications of the simulated data defined in (14), (15), (16), and $\beta_1 = 1$. $\widehat{\beta}$ is the shrinkage estimator defined in (4).

Table 6. Rejection Percentages of the FD Estimator under the Null

		ϕ_Z								
ϕ_ε	n	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.1	100	6.64	6.28	6.20	5.40	6.16	6.12	6.18	5.56	5.46
	200	6.02	6.02	5.44	5.26	5.92	5.58	5.58	5.08	4.74
	400	5.38	4.80	5.66	5.30	5.34	5.22	5.18	5.36	5.16
0.2	100	6.26	6.46	5.80	5.44	5.86	6.46	5.98	5.62	6.28
	200	5.70	5.62	5.50	6.02	4.96	5.46	5.78	4.28	5.32
	400	5.62	5.32	5.14	5.24	5.38	5.08	5.38	5.14	5.20
0.3	100	5.88	6.44	6.00	5.86	6.28	5.62	5.34	5.92	5.32
	200	6.06	5.26	5.08	5.34	5.06	5.22	5.48	5.48	5.54
	400	5.20	4.98	5.30	5.44	4.98	5.20	5.32	5.80	4.92
0.4	100	6.44	6.14	5.96	6.46	5.60	6.56	6.02	5.74	5.74
	200	5.76	6.22	5.72	5.18	5.78	5.34	5.26	5.42	4.84
	400	5.30	5.18	4.96	5.12	4.72	4.58	4.70	5.10	5.08
0.5	100	5.96	5.64	5.84	5.66	5.64	5.52	5.32	5.64	5.30
	200	5.44	5.42	5.38	5.60	5.32	5.68	5.52	5.20	5.60
	400	4.82	4.68	5.26	5.12	5.32	4.78	5.38	5.24	5.12
0.6	100	5.36	5.78	6.02	5.96	5.68	5.82	6.08	5.66	5.74
	200	5.22	5.36	5.74	5.62	5.28	5.34	5.50	5.56	5.04
	400	5.50	5.20	5.22	4.72	4.94	5.18	4.76	5.52	5.04
0.7	100	6.06	5.28	5.86	6.36	5.54	5.20	5.36	6.20	5.42
	200	5.52	5.64	5.46	5.62	5.26	5.22	5.96	5.40	5.46
	400	5.10	5.14	4.90	5.80	5.12	5.62	5.34	5.40	5.24
0.8	100	6.24	5.96	6.14	5.62	5.98	5.34	5.66	5.52	6.14
	200	5.50	5.28	5.22	5.78	5.74	4.94	5.12	5.18	5.10
	400	5.38	5.56	5.04	5.30	5.42	5.34	4.90	5.30	4.82
0.9	100	5.70	5.58	5.58	5.54	5.36	6.12	6.70	5.86	5.68
	200	5.68	5.48	5.64	5.64	5.78	5.72	5.52	5.38	5.52
	400	5.48	5.36	5.44	5.20	4.74	5.26	5.20	5.18	5.24

Notes: All the results are based on 5,000 replications of the simulated data defined in (14), (15), (16), and $\beta_1 = 1$. $\widehat{\beta}$ is the shrinkage estimator defined in (4).

Table 7. Emprical Power Performance of Three Estimator: $n = 200$

		ϕ_Z								
ϕ_ε	Estimator	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.1	OLS	29.36	27.68	28.96	28.44	28.42	28.10	27.66	27.76	29.02
	FD	23.56	20.94	19.44	18.94	17.24	14.98	12.60	9.14	7.72
	$\widehat{\beta}$	29.98	29.02	29.64	29.48	29.22	28.86	28.38	28.30	29.24
0.2	OLS	28.66	28.38	27.18	26.48	26.80	25.38	25.74	24.54	24.60
	FD	24.72	23.80	22.20	20.46	18.76	15.70	13.38	10.38	7.94
	$\widehat{\beta}$	30.74	30.62	28.64	29.30	28.24	26.48	26.48	25.58	25.36
0.3	OLS	28.72	26.62	26.42	25.12	24.60	23.58	23.04	22.96	22.76
	FD	30.10	27.70	24.18	22.06	20.54	17.20	14.44	11.32	8.86
	$\widehat{\beta}$	33.62	31.80	29.94	29.32	27.76	26.74	24.72	23.82	23.26
0.4	OLS	28.86	26.92	25.80	23.88	23.80	21.32	20.32	19.68	20.10
	FD	34.92	31.76	27.72	25.06	23.48	19.40	15.82	12.68	8.84
	$\widehat{\beta}$	37.38	34.94	32.18	30.10	29.60	26.28	23.16	21.70	21.66
0.5	OLS	29.48	26.58	26.02	22.06	21.14	19.50	19.46	19.28	18.78
	FD	40.70	37.56	35.56	30.30	26.54	22.56	18.56	13.80	10.00
	$\widehat{\beta}$	42.90	39.86	38.12	33.14	30.44	27.68	24.84	23.18	20.76
0.6	OLS	28.30	26.10	23.98	22.34	20.70	18.54	18.12	17.24	17.14
	FD	51.12	45.40	41.98	36.52	32.22	26.98	21.44	17.02	10.88
	$\widehat{\beta}$	52.64	46.96	43.68	40.02	35.18	30.42	26.22	23.14	18.92
0.7	OLS	28.62	26.32	23.28	21.18	20.04	17.58	16.74	15.56	15.60
	FD	63.16	59.12	52.12	47.18	43.14	34.92	28.52	21.18	12.72
	$\widehat{\beta}$	63.60	59.58	53.46	48.38	44.70	37.80	30.98	24.80	19.00
0.8	OLS	29.54	26.42	23.84	21.52	18.28	16.80	16.20	15.00	14.80
	FD	81.52	78.10	71.24	67.04	57.90	48.72	39.06	27.80	17.02
	$\widehat{\beta}$	81.78	77.90	71.80	67.54	58.66	49.28	40.88	30.64	20.86
0.9	OLS	33.54	29.70	26.54	22.28	19.32	16.86	15.88	14.78	14.78
	FD	98.18	97.22	94.74	91.14	87.20	78.24	68.30	50.32	29.22
	$\widehat{\beta}$	98.16	97.22	94.74	91.02	87.06	78.36	68.34	50.86	31.12

Notes: All the results are based on 5,000 replications of the simulated data defined in (14), (15), (16), and $\beta_1 = 0.9$. $\widehat{\beta}$ is the shrinkage estimator defined in (4).

Table 8. Emprical Power Performance of Three Estimator: $n = 400$

		ϕ_Z								
ϕ_ε	Estimator	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.1	OLS	50.36	50.90	49.90	48.82	48.72	46.98	46.46	46.96	46.58
	FD	39.36	36.76	34.60	30.86	27.54	24.02	18.60	15.04	9.76
	$\widehat{\beta}$	51.82	51.94	50.76	49.90	49.48	47.84	47.28	47.58	47.04
0.2	OLS	51.26	49.40	47.70	46.04	44.72	43.10	42.30	40.62	40.52
	FD	45.04	42.04	37.58	34.50	30.72	25.82	22.36	16.38	11.12
	$\widehat{\beta}$	54.34	53.08	50.42	48.84	48.22	45.58	44.14	41.76	41.26
0.3	OLS	48.56	48.56	45.40	42.88	40.50	39.96	37.82	36.62	35.00
	FD	50.94	47.80	42.46	38.52	33.50	28.82	23.56	18.10	11.60
	$\widehat{\beta}$	57.30	55.84	51.90	49.52	46.08	44.50	41.76	39.20	36.38
0.4	OLS	48.82	45.12	44.58	41.60	37.00	35.64	32.58	33.20	30.26
	FD	58.74	52.80	48.46	45.34	38.04	32.32	26.78	20.14	13.04
	$\widehat{\beta}$	62.40	58.24	55.92	53.20	46.44	44.22	38.82	37.32	32.28
0.5	OLS	47.62	45.52	40.56	38.20	35.28	32.48	29.78	28.04	26.66
	FD	66.78	62.92	57.44	52.74	46.14	39.26	31.84	24.20	13.80
	$\widehat{\beta}$	69.44	66.00	60.86	58.06	52.48	46.84	41.46	36.20	30.10
0.6	OLS	48.14	43.38	39.70	35.92	33.14	29.40	26.16	24.48	21.58
	FD	78.54	72.40	68.66	62.86	57.08	46.24	37.78	28.64	16.44
	$\widehat{\beta}$	79.66	73.80	71.06	65.20	60.40	50.70	44.58	36.62	27.68
0.7	OLS	47.60	42.58	38.46	34.02	29.92	26.00	23.94	21.22	18.72
	FD	89.62	86.28	81.32	76.10	67.50	59.58	49.20	35.32	20.72
	$\widehat{\beta}$	89.96	87.06	82.08	77.22	69.20	62.36	52.32	40.40	28.72
0.8	OLS	46.02	41.84	37.76	33.78	27.62	24.96	21.86	17.80	17.54
	FD	98.02	96.54	94.54	91.58	85.84	77.22	66.34	48.30	29.16
	$\widehat{\beta}$	98.06	96.70	94.66	91.96	85.90	77.44	67.66	51.50	33.90
0.9	OLS	48.78	44.32	38.14	31.92	28.00	22.62	19.26	15.96	14.38
	FD	100.00	99.96	99.94	99.54	99.30	97.42	92.30	79.22	50.80
	$\widehat{\beta}$	100.00	99.96	99.94	99.56	99.26	97.44	92.24	78.90	52.10

Notes: All the results are based on 5,000 replications of the simulated data defined in (14), (15), (16), and $\beta_1 = 0.9$. $\widehat{\beta}$ is the shrinkage estimator defined in (4).

Table 9. Empirical Power Performance of the Shrinkage Estimator relative to both the OLS and FD Counterparts

	ϕ_Z								
ϕ_ε	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
					$n = 200$				
0.1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.3	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.4	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.5	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.6	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.7	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.8	1.0000	0.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.9	0.0000	1.0000	1.0000	0.0000	0.0000	1.0000	1.0000	1.0000	1.0000
					$n = 400$				
0.1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.3	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.4	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.5	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.6	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.7	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.8	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
0.9	1.0000	1.0000	1.0000	1.0000	0.0000	1.0000	0.0000	0.0000	1.0000

Notes: The results are based on the findings in Tables 7 and 8. The value of each entry equals 1 when the power of the shrinkage estimator is better than that of the OLS and that of the FD estimators at the same time. Otherwide, it equals 0.

行政院國家科學委員會補助國內專家學者出席國際學術會議報告

97 年 9 月 2 日

報告人姓名	郭炳伸	服務機構及職稱	國立政治大學國貿系教授
會議 時間 地點	27-31 August, 2008 University of Bocconi, Milan, Italy	本會核定補助文號	NSC 97-2752-H-004 -002 -PAE
會議名稱	European Meeting of the Econometric Society		
發表論文題目	A Simple Hybrid Bootstrap Test for Prediction Ability Based on Autoregressions		

一、參加會議經過

本次歐洲計量會議仍然和往常一樣，係與歐洲經濟學會（European Economics Association）合辦，是年度全球經濟學界的盛會。今年由義大利米蘭的 Bocconi 大學承辦。該大學係負有盛名的商業大學，在全球的各項排名（Financial Times 或 Newsweek）名列前矛。本校商學院亦在前年與該校簽下交換學生約定，本校的各字在該校入口處可以很清楚地被發現。Bocconi 大學由於辦學優秀，捐錢甚多，今年的會議地點就是在該校甫興建完成的新大樓舉行。該大樓的恢宏氣度，好似國家藝術殿堂，從任何角度觀看，皆有不同的風貌，令人稱羨。由於本會議與 EFA 合辦，人數與規模皆屬驚人，其主要的外部利益是邀請來的會議專題演講者多且精。我所參加過的三場，主講人皆能在短短一個半小時中，以非常平易近人的方式交代過去與未來的研究輪廓。這樣的表達（presentation）技巧，出神入化，值得終身效法。

二、與會心得

在這次會議中，有許多的主題令人耳目一新。例如，有討論人格形成與教育資源關係的各項研究。還有的是，為迎接行為經濟學的掘起，重新思考如何衡量福利水準與政策成效，也是會議多場討論的焦點。我嘗試參加聆聽若干場次的論文發表，但囿於專業領域不同，所獲有限。但是可以感受的是，在打破人類行為不全然理性的思維下，許多微觀研究皆以嶄新的方式重新探討既有的問題。其研究趨勢儼然成形，後繼對總體或計量的影響為何，值得進一步追蹤觀察。

與本人研究相關的議題在會議中仍在許多場次有論文發表。茲將重要心得摘結如下：

一、Prof. Baltagi 利用橫斷面資訊進行預測。Prof. Baltagi 係追蹤資料模型的重要研究先驅。如今他也注意到來自橫斷面的資訊可以提昇預測準確度。他的模擬清楚的顯示，若沒有考慮橫斷面資訊，預測準確性將大幅下滑。這樣的發現與本人的國科會這次卓越計劃的研究成果不謀而合。主要的差別只是在於我們將這樣的概念直接應用於匯率預測上，而 Prof. Baltagi 則是利用模擬資料進行研究。

二、利用橫斷面資訊進行時間數列性質的檢測，依然是焦點議題。至少有八篇文章，以不同方式結合橫斷面資訊，產生新的檢定，企圖以更有效的方式偵測出時間數列的恆定性質。不

過這些檢定具有一樣的瑕疵，也就是一旦這些檢定無法接受虛無假設時，其所呈現的訊息，只是橫斷面中至少有一數列無法滿足虛無假設，但究竟是哪一數列無從得知。這對實證研究者事實上並無太大幫助。在許多實證研究中，比如實質匯率的購買力平價說檢定，我們感到興趣的是「特定」實質匯率是否具有恆定性質，而非前述橫斷面檢定所得到的籠統訊息。

三、考察參觀活動(無是項活動者省略)

無。

四、建議

五、攜回資料名稱及內容

本會議議程。

六、其他

無。