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(1/4)
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 ： 國外研究心得報告
出席國際會議研究心得報告及發表論文

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中 華 民 國 96 年 02 月 07 日

※大學學術追求卓越發展延續計畫執行報告格式

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

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

I		COVER
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III	**FORM2**	LIST OF WORKS, EXPENDITURES, MANPOWER, AND MATCHING SUPPORTS FROM THE PARTICIPATING INSTITUTES（REALITY）.
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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 (1/4)

Understanding Exchange Rate Predictability: The Role of Estimation Risk (1/4)

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

Overall Duration: Month 04 Year 2006 - Month 03 Year 2010

Report Duration: Month 04 Year 2006 Month 03 Year 2007

National Chengchi University

Jan., 2007

II. (FORM1) BASIC INFORMATION OF THE PROGRAM

Program Title: 匯率預測：估計風險之角色 (1/4) Understanding Exchange Rate Predictability: The Role of Estimation Risk (1/4)					
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	664	3	3
		-		-
		-		-
		-		-
Overall	1052	664	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	516	148	0	0	664	1	0	3	0	4	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			1			
	TECHNOLOGY REPORTS						
PATENTS	PENDING				-		
	GRANTED				-		
COPYRIGHTED INVENTIONS	ITEM						
WORKSHOPS/CONFERENCES[3]	ITEM		1				
	PARTICIPANTS		Around 20				
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 is to argue 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.

2. Breakthroughs and Major Achievements

The evidence for the exchange rate predictability in the past literature has not been consistent. In contrast, the current project, however, after controlling the estimation risks, is able to establish evidence for the predictability, whether the forecasting horizons are short or long. In addition to evidence for the predictability, at least two major conclusions emerging from the research 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 panel data has not been effectively made use of. The development of a new shrinkage estimator, as an important technical innovation in the current project, thus, is to be able to control the estimation risk by pooling information from panel data smart.

3. 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.

3.1 Development of a shrinkage estimator:

A shrinkage 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.

To reduce the estimation risks, the shrinkage estimator is considered. It is a Stein-like estimator which linearly 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 shrinkage 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 shrinkage 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 shrinkage estimator has the advantages of producing more reasonable slope estimates.

3.2 Risk reduction: simulation analysis

We examine 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 document that the shrinkage estimator empirically dominates the least-square estimator, regardless of which simulation scenario is considered. Virtually the risk reductions using the shrinkage estimator can be as large as between 10\% and 35\%. In addition, The risk improvements of the shrinkage estimator is embodied further into power gains in testing. Our simulation shows that the power gains from using the shrinkage estimator is 10\% or more in many cases. An implication of the finding is merely that the predictability alternative can now be better detected from the data when the test statistics are based on the shrinkage estimator.

3.3 A re-examination of the exchange rate predictability

We re-examine the empirical validity of the exchange rate predictability applying the shrinkage 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. There are additional considerations for the use of the bootstrap. The asymptotic theory for the proposed estimator has not been established yet. It is expected that the asymptotic distributions of the statistics based on the shrinkage estimator is ill approximated by the normal, because of the high degree of persistence characteristic in predictors.

We access 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 stronger evidence presented for the dominance of the monetary model over the random walk, after accounting for estimation risks using the shrinkage estimates. With few exceptions, the p-values associated with the shrinkage estimates for both statistics are smaller, relative to those associated with the least square estimates.

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 no 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 long-horizon.

Clearly, by adjusting for the estimation risks, the evidence that the fundamentals help forecast the exchange rate at short or even long horizon is stronger and clearer.

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

The mini conference held at Academia Sinica in Jan this year exposed me to the ideas contributed by other principle investigator from different sub-projects. I had to admit that 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.

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

The current results from the first-year project are empirically oriented. While I have had the intuitions that the new shrinkage estimator employed in the project might do well in empirical application, the statistical properties of the estimator remains largely unexplored. This will be the goal for the projects for the years to come. And the research will be very challenging but worthwhile. It is worthwhile because little econometric research has been done in the context of the predictive regressions with near unit root regressors using an estimator like we adopted where the information from both univariate time series and the cross-sections are effectively utilized. It is challenging because the suggested estimator is essentially of non-linear nature that will much compound the whole asymptotic analysis in the context of the predictive regressions with highly persistent regressors.

6. International Cooperation Activities (Optional)

The first-year project was presented at an econometric conference held in London. I got instant comments from Prof. Hashem Pesaran from Cambridge University, and also conversed with him during the break. Prof. Pesaran has been the editor of Journal of Applied Econometrics for years, and has made quite a few important contributions to the econometrics and macroeconomics literature. His responses to my paper were quite encouraging ,as he showed a great interest in the development and the applications of the estimator. He also commented that the way the estimator combining the information from data is very much similar to what the practitioners do, i.e. combining information from different sources available. I am planning to visit Cambridge and am hoping to be able to work with him on the subject, if the funding is sufficient.

VI. APPENDIX I: MINUTES FROM PROGRAM DISCUSSION MEETINGS

VII. APPENDIX II:

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

X. APPENDIX V: MIDTERM/FINAL SELF-ASSESSMENT

PROGRAM TITLE: _____

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

REVIEWER'S COMMENTS & SUGGESTION:

PRINCIPLE INVESTIGATOR'S FEEDBACK: (AVAILABLE)

Program Reviewer's Signature:_____

Doing Justice to Fundamentals in Exchange Rate Forecasting: A Control over Estimation Risks

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Jan., 2007

Abstract

A shrinkage estimator that accounts for estimation risks is developed and employed to re-access whether the monetary fundamentals help predict changes in exchange rates. The suggested estimator is featured by optimally pooling information from cross-sections across time and that from the individual time series of concern. While the estimation risk in term of mean squared errors takes place in the presence of parameter uncertainties, it is more problematic in the context of the exchange rate predictive regression where the time series under study are typically short and the predictors are highly persistent. Monte-Carlo simulations clearly demonstrate that comparing to the least-square estimator, the magnitude of estimation errors associated with our shrinkage estimator is 10% to 35% less. Moreover, the risk reductions convert into sizable power gains for tests for predictability, yielding a robust inference. In contrast to the previous studies, a uniform evidence of the higher ability of monetary fundamentals to forecast exchange rate movements is now found at both short and long horizons, whether in-sample or out-of-sample.

Keywords: random walk, fundamentals, exchange rate forecasting, shrinkage estimator, estimation risk, bootstrap
JEL classification: C22, C52, C53, F31, F47

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1 Introduction

Whether economic fundamentals help predict exchange rate movements remains an unsettled issue. Messe and Rogoff in a series of papers in 80s first demonstrated that a simple random walk forecast of the exchange rate outperforms alternative competing models based on economic theories. This is to say that economic fundamentals such as money supplies, interest rates and outputs simply contain little information in explaining future changes in exchange rates, an evidence for the failure of the economic models. Some subsequent studies do find success for fundamentals-related models that improve upon random walks out-of-sample. Yet, the results do not lend enough credence to shaking the puzzling fact that the exchange rates can be well-approximated as random walks, where their robustness remains to be established. While it is still difficult to attribute fundamentals to changes in exchange rates empirically, a recent theory of Engel and West (2004) justifies the near random-walk behavior of the exchange rate, even in the presence of a link between exchange rates and fundamentals.

Our study is motivated by one of the key assumptions on which the theory of Engel and West is built: Fundamental variables have autoregressive unit roots. We take the assumption as a natural beginning point of the study, and want to explore its empirical implications in the predictive regressions used in the literature. In contrast to economic theory of Engel and West, the paper attempts to offer econometric explanations to the near random-walk exchange rates, and argues that previous empirical evidence for or against predictability in exchange rate movements might have been considerably flawed by an existence of estimation risk due to the strong persistence in fundamentals. The primary goal of the paper is in a pursuit of a more reliable inference procedure for the predictability both in-sample and out-of-sample by appropriately controlling for the estimation risk.

The persistence nature in fundamentals has created subtle problems for estimation of and inference for the economic models. As one outstanding aspect of the problems, when fundamentals are highly persistent, the OLS estimates are very likely to subject to small-sample bias (Stambaugh, 1999). To correct for the bias, previous work appeals to the bootstrap techniques (for example, Mark, 1995; Kilian, 1999). Although the bootstrap helps reduce the bias, it introduces additional errors due to the bias estimation. On the

other hand, the persistence may lead to a substantial amount of variations in parameter estimation in the region of near unit root, implying an efficiency loss (Phillips, 1998). As a consequence of the loss, inferences for forecasting performance might well be biased in favor of random walks, even when the data are generated by the fundamentals-based models (Rossi, 2005). Nevertheless, it is well-known that there is a clear trade-off between bias and estimation errors in small samples. Thus, much previous work just provides partial answers to the predictability at issue by only looking at either bias or estimation errors. Little existing work however investigates how the tradeoff would impact on model estimations and forecasting inference.

The paper deals with both problems with small-sample bias and with estimation errors by proposing a shrinkage estimator. The shrinkage estimator is derived by minimizing mean-squared forecasting errors in the spirit of Judge and Mittelhammer (2004), and thus can properly take into account the tradeoff. Specifically, the proposed estimator is an optimal-weighted average of the OLS estimator from a certain exchange rate time series and the grand average of the OLS estimators from the panel of the exchange rates series under study. In this way, we exploit cross-sectional information as those using panel methods (Mark and Sul, 2001), but in quite a different manner. By shrinking the asymptotically unbiased OLS estimator full of estimation errors toward the biased grand average, the estimation risk can now be considerably reduced. Of empirical significance is that the use of the shrinkage estimator can potentially convert the estimation accuracy improvement into power gains for the forecasting ability testing. As a result, when exchange rate variations is predictable, the tests are ought to be more capable of detecting it, and the evidence by tests based on the mounted estimator would tend to be more trustworthy than that presented before. Our simulations clearly demonstrate the merits of the proposed semi-parametric estimator in reducing the estimation risk. Calibrating parameters to the data set that Kilian (1999) examined, our Monte-Carlo study shows that the power gains are found to be between 10% and 30% greater than those using OLS estimates. A technical innovation of our approach lies in an application of the bootstrap to parameter estimations, instead of plugging in consistent estimates as suggested by Judge and Mittelhammer (2004).

Applying the newly developed estimator, we re-access the central issue of the study: whether fundamentals can predict exchange rate movements. We also quantify potential

estimation risk which the previous research using conventional estimators could have been subjected to. Significantly, we find that the fundamentals-based models now consistently perform better than random walks, across various horizons. We conclude that the inability of the economic models to yield better forecasts might well be due to the estimation risk that has not been accounted for.

The remainder of the paper is organized as follows. Section 2 describes the monetary models of exchange rate determination and the corresponding predictive regression. In Section 3 we develop the shrinkage estimator used in the paper. Section 4 numerically analyzes the statistical advantages of the shrinkage estimator over the conventional estimator. Section 5 re-examines the exchange rate predictability, and presents the empirical findings. Finally, Section 6 concludes. Technical descriptions of the shrinkage estimator is left to the appendix.

2 A monetary model of exchange rates and its VAR representation

We consider a standard long-run models of exchange rates where purchasing power parity and uncovered interest parity are assumed to hold. Let e_{it} be the log nominal exchange rate at time t between currency i and the benchmark currency, denoted by '0'. The exchange rate is currency i price of a unit of currency 0. Let r_{it} be the nominal interest rate and p_{it} be the price level associated with currency i respectively. Thus,

$$r_{it} - r_{0t} = \mathrm{E}_t e_{it+1} - e_{it}, \tag{1}$$

$$e_{it} = p_{it} - p_{0t}, \tag{2}$$

where E_t is the conditional expectation operator.

When money markets, both domestic and foreign, are in equilibrium,

$$m_{it} - p_{it} = \lambda\, y_{it} - \phi\, r_{it}, \tag{3}$$

$$m_{0t} - p_{0t} = \lambda\, y_{0t} - \phi\, r_{0t}, \tag{4}$$

where m_{it}, y_{it} and p_{it}, respectively, are the log of money supply, output and price level of currency i. The analogous variables for currency 0 are m_{0t}, y_{0t}, and p_{0t}. Both money equations share common income elasticity λ and interest semi-elasticity ϕ. Combining (1),

(2), (3) and (4),

$$\mathrm{E}_t e_{it+1} - e_{it} = \mathrm{E}_t \triangle e_{it+1} = -\frac{1}{\phi}\left(f_{it} - e_{it}\right) = -\frac{1}{\phi} x_{it}, \tag{5}$$

where $f_{it} = (m_{it} - m_{0t}) - \lambda(y_{it} - y_{0t})$ is the monetary fundamental values, and thus $x_{it} = f_{it} - e_{it}$ is the deviation of the exchange rate from its fundamental value. The equivalence relation simply states that the exchange rate is expected to react to deviations from its fundamentals. The no bubble solution to the expectation difference equation (5) would deliver the present value model:

$$e_{it} = \frac{1}{1+\phi} \sum_{j=0}^{\infty} (\frac{\phi}{1+\phi})^j \mathrm{E}_t f_{it+j}.$$

Deducting f_{it} from both sides gives

$$e_{it} - f_{it} = \sum_{j=1}^{\infty} (\frac{\phi}{1+\phi})^j \mathrm{E}_t \triangle f_{it+j}.$$

These equations make it easy to explain a long-run equilibrium relation between exchange rates and the monetary fundamentals. As long as f_{it} is non-stationary processes, e_{it} is an I(1) process and $f_{it} - e_{it}$ is an I(0) process by the aforementioned relation. As a result, there is a cointegration between e_{it} and f_{it} with the pre-specified cointegrating vector (1,-1). Using the VAR framework, the cointegration implies a bivariate vector error correction representation for $y_{it} = (e_{it},\ f_{it})'$: $y_{it} = c_0 + c_1 y_{it-1} + \cdots + c_p y_{it-p} + \varepsilon_{it}$. Some re-arranging can yield another vector error correction (VEC) model for e_{it} and x_{it}.[1] In particular, our econometric analysis centers on a VEC model that is frequently used in the exchange rate forecasting literature:

$$\triangle e_{it} = \beta_i^{(1)} x_{it-1} + \varepsilon_{it}^1, \tag{6}$$

$$\triangle x_{it} = \alpha_i x_{it-1} + \sum_{l=1}^{p_i} c_{il}^2 \triangle e_{it-1} + \sum_{l=1}^{p_i} d_{il}^2 \triangle x_{it-1} + \varepsilon_{it}^2, \tag{7}$$

where $(\varepsilon_{it}^1,\ \varepsilon_{it}^2)$ are assumed to be i.i.d. with a vector mean zero and a nonsingular covariance matrix. Equation (6) is the short-horizon predictive regression employed by Mark (1995), Berkowitz and Giorgianni (1997), Groen (1997), Kilian (1997), Berben and Dijk (1998) and Mark and Sul (2001) to study the exchange rate predictability. One of the goals of these studies as well as ours is to investigate if the mean reversion of x_{it} can improve the forecast

[1] This follows by noting that $\triangle x_{it} = \triangle f_{it} - \triangle e_{it}$.

accuracy by testing for $\beta_i^{(1)} = 0$ against $\beta_i^{(1)} > 0$. The positive sign of the slope coefficient $\beta_i^(1)$ suggests that e_{it} is expected to decline when above its fundamentals. Both equation (6) and (7) serve as data generating process in our bootstrapping algorithm after fitting them to the data. Because the log exchange rate returns to its fundamental value over time, more than 1-period ahead change in e_{it} may be characterized by deviations from the monetary fundamentals as well. Thus, the predictive regression (6) can in general be of the form:

$$e_{it} - e_{it-k} = \beta_i^{(k)} x_{it-k} + \varepsilon_{it}, \tag{8}$$

where k represents the forecast horizons and is set to 1, 4, 8, 12 and 16 in the analysis. Not to complicate the use of notations, the superscript (k) will be saved from the exposition following, unless there are confusions created.

Our analysis takes up two major related empirical concerns. As stated above, one would be to search for the empirical validity for the monetary model of exchange rates using our proposed estimator. By controlling for the estimation risk, the estimator is hoped to achieve a high degree of statistical accuracy in establishing the proposition. Moreover, the previous discussions suggest that for exchange rate to be predictable, exchange rates are ought to be cointegrated with the monetary fundamentals first. Therefore, another task is to investigate the existence of the cointegration between e_{it} and f_{it} based on the suggested estimator.

3 Econometric Framework

This section develops a shrinkage estimator that is to control potential estimation risks associated with the predictive regression. The motivation for a need for the estimator will be discussed immediately.

3.1 Sources of estimation risk

The OLS estimation of the slope coefficient tends to suffer more estimation risk than ordinary regressions. It results from some distinctive characteristics for the predictive regressions. First, the predictor x_{it}, or the deviation of exchange rate from fundamentals, is documented to be a highly persistently process. The high degree of persistence in forecasting variables, however, may generate a biased estimate of β_i in small samples, although do not alter the unbiasedness asymptotically. The magnitude of the bias is positively proportional to the

degree of persistence in forecasting variables for a given sample size, as demonstrated by Stambaugh (1999).

Second, the predictor possesses a much smaller variability than the dependent variable does (Mark and Sul, 2004). It is regarded that the small variance might not affect some statistical properties of the estimators asymptotically. But in finite samples, a small variance in regressors suggests a small signal-to-noise ratio, yielding imprecise estimates of β_i. It turns out that the imprecision could not be safely ignored when taking into account another key feature of predictive regressions as below.

Third, the dependent variable is long-horizon change in log exchange rate that amounts to overlapping sums of short-horizon change in log exchange rates. Valkanov (2003) have shown that in some parametric settings, the OLS estimator of β_i might be inconsistent, when the link of the small variance in predictors to the overlaps in dependent variables is considered. In other words, the small-sample distributions of the estimates of β_i is more dispersed with the forecast horizon k. This is simply another reflection of the imprecise estimation of β_i due to the small variance.

The estimation risk appears to take a form of either bias or inefficiency, whether it is due to the high persistence or the small variability. The little consensus emerging from empirical findings in the literature may come from the fact that econometric methods adopted can only deal with some parts of the risks. It is thus important to have a comprehensive approach that is capable of controlling for the overall estimation risks. This will be the subject to be studied in the next subsection.

3.2 A shrinkage estimator

To reduce the estimation risks in the context of predictive regressions, we consider a shrinkage estimator for β_i defined by

$$\tilde{\beta}_i = \omega_i \cdot \hat{\beta}_i + (1 - \omega_i) \cdot \bar{\beta},$$

where ω_i is the 'shrinking factor' that assigns weights to the two estimators in combination, $\hat{\beta}_i$ is the OLS estimator, and the grand average estimator is given by

$$\bar{\beta} = \frac{\sum_{i=1}^{N} \hat{\beta}_i}{N}$$

which takes the average of all the OLS estimators of the slope coefficients of the N countries. As it appears now, the shrinkage estimator considered is a Stein-like estimator which linearly combines two alternative estimators that differ in their bias and precision characteristics. Stein (1956) showed that shrinking sample means toward a fixed constant, under some conditions, can reduce estimation risks. The key is to create a tradeoff between bias and accuracy by introducing a biased estimator, represented by the fixed target, to combine with the unbiased estimator, represented by the sample mean. The statistical decision theory suggests the existence of an interior optimum in the tradeoff between bias and precision. Taking a proper weighted average of the unbiased and the biased estimators would constitute one of feasible approaches to attaining the optimal tradeoff. The idea of shrinkage has been widely applied to the problem of portfolio selection (for example, Jorion, 1985; Dumas and Jacquillat, 1990) and the context of prediction (Copas, 1983).

Our shrinkage estimator inherits the idea of Stein's (1956) seminal work. To see this, it is important to recognize that 1) the individual OLS estimator of the slope coefficient is unbiased asymptotically, but has lots of estimation errors due to the small variance of and high degree of persistence of the predictors, and that 2) the opposite is true for the grand average of all the cross-sectional slope estimators which is subject to larger bias but less estimation errors due to the averaging. Thus the intuition of the theory simply suggests that taking a weighted average of the OLS estimator and the grand mean estimator is likely to yield an estimator with less risk in the context of predictive regressions.

It is evident that the suggested estimator for the slope coefficients utilizes information from cross-sections in a similar way that the panel-based estimators adopted by Groen (2000) and Mark and Sul (2001) do. Like Stein, we are concerned with the estimation of several unknown coefficients. It is natural that these Stein-like estimator makes best use of existing information available. 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. The panel-based estimators are built on the assumption that the slope coefficients are all the same for all the cross-sectional countries. The panel approach to pooling the data produces a single estimate. On the other hand, the shrinkage 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 shrinkage

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 shrinkage estimator has the advantages of producing more reasonable slope estimates. When the truth is that the slope coefficients are all the same across each cross-sectional countries, the difference between the slope estimates from the two approaches should be insignificant, because by definition the shrinakge estimator embraces the extreme situation. But if the slope parameters are all different in each country, the panel approach by no means gives consistent slope estimate, because of a false constraint imposed in estimation, while our shrinkage estimator still does, as will be shown below.

The construction of the shrinkage estimator opens a few questions to be answered.

3.3 Shrinkage target

What is the rationale behind the choice of the grand average as the shrinkage target? The grand average has been commonly employed in the literature. Lindley (1962) demonstrates that the risk dominance of the Stein estimator when shrinking the sample mean toward the grand mean estimator. Our choice reflects a belief that the slope coefficients is different and near to each other. Like the constant target in the case of sample mean estimation, the grand average plays the role of a restricted estimator, while the OLS estimator is the unrestricted counterpart. Here the constraint imposed into our estimator is the slope coefficients of all the country are the same. Conventional econometric wisdom would suggest that imposing any structure or restriction in estimation brings forth efficiency gains, whether or not it is true. Consequently, our shrinkage estimator performs best when each of the slope coefficients coincides.

Alternative shrinkage targets as structures or constraints might exist. One shrinkage target works well for a certain data set, but not necessarily for another. It is thus difficult to tell which one works well a priori, without checking out-of-sample performance. This study looks at a dataset of aggregate time series from major developed countries. Within the circle, the transmission of shocks to fundamentals to exchange rates, if any, may vary with the macro environment or the aggregate policy in each country, but at a similar speed. The assumption of the slope heterogeneity is considered a reasonable one. We will show the advantages of the chosen target through simulations.

3.4 Shrinking factor

Applications of the shrinkage estimator is not possible without knowing the shrinking factor ω_i. The subsection is devoted to how to determine and estimate it. The major goal for all the existing estimators is in finite samples to minimize the estimation risk of the proposed estimators. This entails a need to specify a loss function. We propose to use the quadratic loss function. The loss function considers the tradeoff between bias and estimation errors using a quadratic distance measure between the true and the estimated slope coefficient. It gives rise to a risk function that calculates mean squared errors (MSE) as follows:

$$\Re(\tilde{\beta}_i, \beta_i) = \mathrm{MSE}(\tilde{\beta}_i) = \mathrm{E}\left[(\tilde{\beta}_i - \beta_i)^2\right].$$

Minimizing $\Re(\tilde{\beta}_i, \beta_i)$ with respect to ω_i gives

$$\omega_i = \frac{\mathrm{MSE}(\bar{\beta}) - E\left[(\hat{\beta}_i - \beta_i)(\bar{\beta} - \beta_i)\right]}{\mathrm{MSE}(\hat{\beta}_i) + \mathrm{MSE}(\bar{\beta}) - 2E\left[(\hat{\beta}_i - \beta_i)(\bar{\beta} - \beta_i)\right]}.$$

We can describe the 'optimal' shrinking factor further, provided that the probability structure between the estimators is given. Without assuming normality, suppose the OLS estimator and the grand average in finite samples is jointly distributed as:

$$\begin{bmatrix} \hat{\beta}_i \\ \bar{\beta} \end{bmatrix} \sim \mathrm{P}\left[\begin{pmatrix} \beta_i + \gamma_{i,ls} \\ \beta_i + \gamma_{i,g} \end{pmatrix}, \begin{pmatrix} \sigma^2_{i,ls} & \rho_i \\ \rho_i & \sigma^2_{i,g} \end{pmatrix}\right],$$

where P can be any distribution function as long as the first and second moments exist and are finite, and , and β_i is the true value of the slope coefficient i. Note that $\gamma_{i,ls}$ is the bias associated with the OLS estimator due to the high degree of persistence in predictors, and $\gamma_{i,g} = \frac{\sum_i \beta_i}{N} - \beta_i$, the distance of the true grand average from the true slope coefficient i. Therefore, when the slope coefficients are all the same, $\gamma_{i,g} = 0$. A important feature from the covariance matrix is to have the considered estimators correlated by an introduction of ρ_i. The appearance of the correlation measure is unusual when understanding the shrinkage estimator in an empirical Bayesian vein where it combines a prior, given by the grand average estimate, with the sample information corresponding to the least squares estimate. The typical empirical Bayesian approach assumes independence between prior and sample information, regardless of whether the prior is estimated from the same dataset as the grand average. Allowing for a correlation between the combined estimators may avoid damage in

estimations that takes place without considering the link.[2] With some algebra calculations,[3]

$$\omega_i = 1 - \frac{\sigma_{i,ls} + \gamma_{i,ls}^2 - \rho_i - \gamma_{i,ls}\gamma_{i,g}}{\sigma_{i,ls}^2 + \gamma_{i,ls}^2 + \sigma_{i,g}^2 + \gamma_{i,g}^2 - 2\rho_i - 2\gamma_{i,ls}\gamma_{i,g}}.$$

The expression offers some intuitions of how the weight is given to the combined estimators. Higher weight is assigned to the grand average when the OLS estimator has a higher bias and variance. But the estimator is drawn toward the OLS estimator in the case of high correlation between the combined estimators. When there are increases in $\gamma_{i,g}$ or $\sigma_{i,g}^2$, indications that the true slope coefficients are so scattered not as the prior prescribes, the OLS estimator receives more weight. This is because gains from information combination in both cases is small. Thus, very importantly, the weight adapts itself to the data.

It is crucial both in theory and in applications to estimate the shrinking factor consistently. A pre-requisite for establishing the consistency of the proposed estimator is the weight consistency.[4] Further, it controls the information quality represented by the combined estimators. A correct inference from the data is very much dependent on a precisely estimated weight. A technical innovation in this paper is to suggest a consistent bootstrap procedure to estimate the weight parameter. The available estimator as suggested by Judge and Mittelhammer (2004), though consistent, relies on the asymptotic argument, and its finite-sample performance can be satisfactory only when the sample size is sufficiently large. This might not be the case in the study because of a panel of short-spanned time series is under investigation. Typically the bootstrap estimator have proven to display more robust performance than the asymptotic counterpart. A more important justification for such a bootstrap procedure is that no general consistent estimator has been mounted for the bias parameters such as $\gamma_{it,l}$ and $\gamma_{i,g}$. We appeal to the bootstrap procedure in order to render our estimation and inference feasible in the subsequent empirical analysis. Very detailed illustration of the bootstrap algorithm is given in the appendix to save the space.

[2] One more difference is that the Bayesian approach is in general not optimized with any particular loss function.

[3] A detailed derivation is given in the appendix.

[4] We have shown in the appendix the consistency of the shrinkage estimator, given the existence of a consistent estimator for the shrinking factor.

4 Risk reduction: simulation analysis

This section investigates to what extent the proposed estimator can improve over the traditional estimator in terms of risk reduction through simulations. To make our analysis more realistic, the DGP calibrated to the actual data is considered. Further, to permit a direct comparison, the data under simulation analysis now and empirical study later is the same as that used in Kilian (1999).[5] The data spans from 1973.I to 1997.IV, and contains the US dollar exchange rates of the Canadian dollar, the German mark, the Japanese yen, and the Swiss franc. Thus, the country number $N = 4$ in the study.

The DGPs are based on both the restricted VEC model under the null that the exchange rate is unpredictable, and under the alternative that the fundamental helps to predict the exchange rate, on the maintained assumption that the exchange rate and the fundamental are cointegrated. The key difference in generating data under the null or the alternative thus lies in whether β_i is set to 0. The lag orders of $\triangle x_{it}$ is determined using the Campbell-Perron's general-to-specific rule. A seemingly uncorrelated regression is then fit to the data after the lag orders are settled. Each country is estimated a separate DGP, while the residuals are allowed to be dependent cross-sectionally measured by the joint error covariance matrix Σ. Vector sequence of the innovations are now drawn from $N(0, \hat{\Sigma})$, where the covariance matrix is estimated from the SUR residuals. The pseudo observations on $\triangle s_{it}$ and $\triangle x_{it}$ are produced recursively based on the estimated version of (6) and (7). The MSEs under the null and the alternative are computed and recorded individually using the artificial data from 2000 replications.

Table (1) reports the relative empirical risks of the shrinkage estimator and the least-square estimator under the null and the alternative processes, respectively. The important and encouraging message coming out of the simulations is that the shrinkage estimator empirically dominates the least-square estimator, regardless of which simulation scenario is considered. But the dominance weakens slightly as the forecast horizon increases. Virtually the risk reductions using the shrinkage estimator can be as large as between 10% and 35%. A decomposition of the MSE clearly reveals that the risk reductions using the shrinkage estimator attributes much more to the reductions in the estimation errors, implying accuracy

[5] All the data is available and can be downloaded from the homepage of *Journal of Applied Econometrics*.

gains. In some instances, the bias even increases due to use of the shrinkage estimator, although the bias increases do not offset the error reductions.

The risk improvements of the shrinkage estimator is embodied further into power gains in testing. Table (2) presents the size-adjusted empirical power of using the shrinkage estimator as the test statistic against the predictability alternative. An inspection of Table (2) shows that the power gains from using the shrinkage estimator is 10% or more in many cases. For Germany data, the power gain can be even up to 20%. An implication of the finding is merely that the predictability alternative can now be better detected from the data when the test statistics are based on the shrinkage estimator. Plot (1) depicts the clear difference between the finite-sample distributions of the shrinkage estimator and the least-square estimator, based on the Germany data. [6] In which, the distributions of the shrinkage estimator under the null and the alternative are more centered. This is again due to the error reductions, and exactly where power gains come.

5 A re-examination of the exchange rate predictability

We are in a position to re-examine the empirical validity of the exchange rate predictability applying the shrinkage estimator. The testing strategy basically follows that utilized in Mark (1995), Kilian (1999), and Mark and Sul (2001). 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. There are additional considerations for use of the estimator. As discussed, the estimate for the optimal weight is given based on the bootstrap. Next, the asymptotic theory for the proposed estimator has not been established yet. It is expected that the asymptotic distributions of the statistics based on the shrinkage estimator is ill approximated by the normal, because of the high degree of persistence characteristic in predictors.

Before the asymptotic theory for the estimator is derived, inference on the predictability here is mainly drawn from the bootstrap. The bootstrap conducted is very much the same as described in the preceding simulation section, except the step about sampling innovations. Instead of drawing samples from the parametric normal distribution, the re-samples are now

[6] Similar distribution patterns are also uncovered from other country's data. They are not reported here to economize the presentation.

drawn from a sequence of the restricted residual vectors. In other words, a non-parametric bootstrap is employed. The restriction again is no exchange rate predictability, equivalently $\beta_i = 0$.

A by-product of the study is to test whether the exchange rate is cointegrated with the fundamental, based on the shrinkage estimator. This can be done simply by imposing another restriction that $\alpha_i = 0$ in (7) in the aforementioned re-sampling schemes.

5.1 A new look at cointegration

As has been emphasized, when the cointegration between the exchange rate and the fundamental does not come into existence, the exchange rate is simply unpredictable. We report the results for testing for cointegration using the shrinkage estimator in Table (3).

The bootstrap coefficient test easily rejects the null of no cointegration between the exchange rate and the fundamental, mostly at 5% significance level, with the exception of Japan with $k = 12$. The testing results based on R^2 lend additional credibility to the notion of a cointegration between the exchange rate and the fundamental. Most of the corresponding p-values for R^2 are smaller than 5%, remarkably similar to those for the coefficient test.

Some obvious patterns on the estimated coefficients can be summarized from table. The estimates for the slope coefficients are all shrunk further toward the grand average for all the countries and all the forecast horizons (k). In general, the shrinkage estimates are less dispersed than the OLS counterparts. This is to be expected from the shrinkage theorem. For any particular country, the estimated slope coefficients increases as the horizons increases. Nevertheless this should not be interpreted as an evidence for the increased long-horizon predictability, as the cointegration can not be interchanged with the predictability in notions. More importantly, the estimated slope coefficients for any fixed horizon are clearly seen to vary to a certain degree. This appears to be consistent with our prior belief, but contradicts the extreme assumption made in the panel-based approach that the slope coefficients are the same for all the countries.

We now turn to the estimated optimal shrinking factors. The homogeneity in slope coefficients would suggest that the estimated weights are similar in magnitude for any k. A close inspection of the estimates shows however little evidence for the slope homogeneity. In particular, some of the weights for Germany and Japan are negatively estimated. It is due to

that no constraint on the weight to be positive and smaller than one was placed in estimation. Taking the normality approximation, if not too arbitrary, these negative weight estimates are all covered in confidence intervals centered around the origin at 95% level, implying a true weight indifferent from zero. In other words, the grand averages receives most of the weight. Typically this might take place when the least square estimates are not reliable for higher variance or larger bias. These are also the cases where the risk improvements over the least square estimator may be substantial.

5.2 Out-of-sample forecast adjusted for risks

We access the relative forecast accuracy of the two competing models with DM (Diebold and Mariano, 1995) statistic and Theil's U statistic. It should be noted that the problem with estimating the long-run variance precisely often leads to spurious inference, as documented in the literature.

The forecast results are displayed in Tables (4) and (5). The former is based on the DM statistic, and the latter the Theil's U statistic. There is now stronger evidence presented for the dominance of the monetary model over the random walk, after accounting for estimation risks using the shrinkage estimates. With few exceptions, the p-values associated with the shrinkage estimates for both statistics are smaller, relative to those associated with the least square estimates.

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. Instances of this are found more in Table (5) than in Table (4). For example, 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 no 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 long-horizon. Besides, there seems to have evidence of declining p-values as the prediction horizon is increased, especially the results based on the Theil's U statistic for all the countries but Canada. Overall, by adjusting for the estimation risks, the evidence that the fundamentals help forecast the exchange rate at short or even long horizon is stronger and clearer.

6 Conclusion

It is no denying that inference on the exchange rate predictability based on the univariate predictive regression is not trustworthy due to estimation risks. The panel-based approach exploiting cross-sectional information may reduce estimation errors, but incurs another type of estimation risk with the extreme assumption of the parameter homogeneity. The shrinkage approach proposed enjoys risk gains, while allowing for the parameter heterogeneity. Our Monte-Carlo simulations further demonstrate that the merits of applying the shrinkage approach converts into power gains in the testing context. Significant evidence for the exchange rate predictability can now be found at least for short-horizons. Whether there is evidence of higher predictability at longer horizons remains unconfirmed, although more evidence points to be so after controlling over estimation risks.

One interesting question that deserves more research efforts is to investigate the effects of the country number on the robustness of the inference. The shrinkage approach is basically concerned with estimations of many unknown parameters. This is suggestive of further risk improvements from utilizing more cross-sectional information. Rigorous research might address to what degree an increase in country number can help reduce risks, and how much economic value of additional risk reductions is worth.

Appendix 1: Derivation of the shrinking factor

The risk function as defined based on our shrinkage estimator can be expressed as

$$\mathrm{MSE}(\tilde{\beta}(\omega_i)) = \omega_i^2 \mathrm{MSE}(\hat{\beta}_i) + (1-\omega_i)^2 \mathrm{MSE}(\bar{\beta}) + 2\omega_i(1-\omega_i)\mathrm{E}\left[(\hat{\beta}_i - \beta_i)(\bar{\beta} - \beta_i)\right].$$

Minimizing it with respect to ω_i gives the first-order condition as

$$2\omega_i \mathrm{MSE}(\hat{\beta}_i) - (2-2\omega_i)\mathrm{MSE}(\bar{\beta}) + (2-4\omega_i)\mathrm{E}\left[(\hat{\beta}_i - \beta_i)(\bar{\beta} - \beta_i)\right] = 0,$$

from which the optimal shrinking factor can be found

$$\omega_i = \frac{\mathrm{MSE}(\bar{\beta}) - \mathrm{E}\left[(\hat{\beta}_i - \beta_i)(\bar{\beta} - \beta_i)\right]}{\mathrm{MSE}(\hat{\beta}_i) + \mathrm{MSE}(\bar{\beta}) - 2\mathrm{E}\left[(\hat{\beta}_i - \beta_i)(\bar{\beta} - \beta_i)\right]}.$$

as described. Note that

$$\begin{aligned}
&\mathrm{MSE}(\hat{\beta}_i) = \sigma^2_{i,ls} + \gamma^2_{i,ls}, \\
&\mathrm{MSE}(\bar{\beta}) = \sigma^2_{i,g} + \gamma^2_{i,g}, \\
&\mathrm{E}\left[(\hat{\beta}_i - \beta_i)(\bar{\beta} - \beta_i)\right] = \rho_i + \gamma_{i,ls}\gamma_{i,g}.
\end{aligned}$$

Replacing with all the corresponding expressions above in the equation concerning the shrinking factor then complete the derivation.

Moreover, it is easy to show that the optimal weight derived satisfies the second-order condition, because

$$\mathrm{MSE}(\hat{\beta}_i) + \mathrm{MSE}(\bar{\beta}) - 2 \cdot \mathrm{E}\left[(\hat{\beta}_i - \beta_i)(\bar{\beta} - \beta_i)\right] = \mathrm{E}\left[(\hat{\beta}_i - \bar{\beta})^2\right] > 0.$$

In other words, $\tilde{\beta}_i$ is the minimum among all linear combinations of $\hat{\beta}_i$ and $\bar{\beta}$ under the MSE criterion.

Appendix 2: The consistency of the shrinkage estimator

We provide some regularity conditions under which the consistency can be established. Suppose that $T\hat{\sigma}^2_{i,ls} \xrightarrow{p} \sigma^2_{i,ls}$, $T\hat{\sigma}^2_{i,g} \xrightarrow{p} \sigma^2_{i,g}$, and $T\hat{\rho}_i \xrightarrow{p} \rho_i$. Also assume that $\hat{\gamma}_{i,ls} - \gamma_{i,ls} \equiv o_p(T^{-1})$, $\hat{\gamma}_{i,g} - \gamma_{i,g} \equiv O_p(T^{-1})$ and $\hat{\beta}_i - \beta_i \equiv O_p(\sqrt{T}^{-1})$. Then, when $\sigma^2_{i,g} \neq 0$,

$$\begin{aligned}
&\mathrm{plim}(\tilde{beta}(\hat{\omega}_i)) = \mathrm{plim}\left[\hat{\omega}_i\hat{\beta}_i + (1-\hat{\omega}_i)\bar{\beta}\right] \\
=&\mathrm{plim}(\hat{\beta}_i) + \mathrm{plim}\left[\frac{\hat{\sigma_{i,ls}}^2 + \hat{\gamma_{i,ls}}^2 - \hat{\rho}_i - \hat{\gamma}_{i,ls}\hat{\gamma}_{i,g}}{(\hat{\beta}_i - \bar{\beta})^2} \cdot (\hat{\beta}_i - \bar{\beta})\right] \\
=&\beta_i + \frac{O_p(T^{-1}) + o_p(T^{-1}) \cdot o_p(T^{-1}) - O_p(T^{-1}) - o_p(T^{-1}) \cdot O_p(T^{-1})}{O_p(1) \cdot O_p(1)} \cdot O_p(1) \\
=&\beta_i + o_p(1) = \beta_i.
\end{aligned}$$

But if $\sigma^2_{i,g} = 0$, $\hat{\beta}_i - \beta_i \equiv O_p(\sqrt{T}^{-1})$,

$$\begin{aligned}
&\mathrm{plim}(\tilde{\beta}(\hat{\omega}_i)) \\
=&\mathrm{plim}(\hat{\beta}_i) + \mathrm{plim}\left[\frac{T\hat{\sigma_{i,ls}}^2 + T\hat{\gamma_{i,ls}}^2 - T\hat{\rho}_i - T\hat{\gamma}_{i,ls}\hat{\gamma}_{i,g}}{T(\hat{\beta}_i - \bar{\beta})^2} \cdot (\hat{\beta}_i - \bar{\beta})\right] \\
=&\beta_i + \frac{O_p(1) + o_p(1) \cdot o_p(T^{-1}) - O_p(1) - o_p(1) \cdot o_p(T^{-1})}{O_p(1) \cdot O_p(1)} \cdot o_p(1) \\
=&\beta_i + O_p(1) \cdot o_p(1) = \beta_i.
\end{aligned}$$

This proves the consistency for the estimator.

Appendix 3: Bootstrap algorithm to estimating the optimal weight

The bootstrap procedures are to obtain robust estimates of the parameters appearing in the optimal shrinking factor. The detailed illustrations are as follows:

1. Estimate $\triangle e_{it+k} = \beta_i x_{it} + \varepsilon_{it+k}$ and $\varepsilon_{i,t+k} = \sum_{l=1}^{m} \rho_{il}\varepsilon_{i,t+k-l} + v_{i,t+k}$ with OLS, in which the lag order m is chosen by the AIC criteria, and obtain $\hat{\beta}_i$, $\hat{\rho}_{il}$, $\hat{\varepsilon}_{i,t+k}$ and $\hat{v}_{i,t+k}$.

2. Now draw from $\{\hat{v}_{i,t+k}\}$ with replacements, and generate re-samples using the data-generating process: $\triangle e^*_{it+k} = \hat{\beta}_i x_{it} + \hat{\varepsilon}^*_{it+k}$ and $\hat{\varepsilon}^*_{i,t+k} = \sum_{l=1}^{m} \hat{\rho}_{il}\hat{\varepsilon}^*_{i,t+k-l} + \hat{v}_{i,t+k}$.

3. Regress $\triangle \hat{e}^*_{it+k}$ against x_{it} with OLS and obtain the bootstrap estimates of the slope coefficient, denoted by $\hat{\beta}^*_i$.

4. Repeat steps 2 and 3 B_0 times. Now compute the average bias by $\frac{\sum_{b=1}^{B_0} \hat{\beta}_i - \hat{\beta}^*_{i,b}}{B_0}$, and deduct it from $\hat{\beta}_i$. This is the bootstrap bias-corrected estimate for the slope coefficient, labeled as $\hat{\hat{\beta}}_i$. Then the biased-corrected residuals can be computed accordingly by $\hat{\hat{\varepsilon}}_{it+k} = \triangle e_{it+k} - \hat{\hat{\beta}}_i x_{it}$.

5. Now generate the bootstrap samples based on $\hat{\hat{\beta}}_i$, $\hat{\hat{\varepsilon}}_{i,t+k}$, x_i as if they are true ones by repeating B_0 times steps 2, 3, and 4. Thus, a sequence of $\{\hat{\hat{\beta}}^*_i\}$ is generated. Repeat the same procedures for different countries other than i, and obtain the bootstrap grand average sequence of $\{\bar{\bar{\beta}}^*\}$ for the N countries.

Based on the two sequences of $\{\hat{\hat{\beta}}^*_i\}$ and $\{\bar{\bar{\beta}}^*\}$ obtained from the aforementioned procedures, the bootstrap estimate for the derived optimal shrinkage factor is computed as

$$\hat{\omega_i}^* = \frac{\sum(\bar{\bar{\beta}}^* - \hat{\hat{\beta}}_i)^2 - \sum(\hat{\hat{\beta}}^*_i - \hat{\hat{\beta}}_i)(\bar{\bar{\beta}}^* - \hat{\hat{\beta}}_i)}{\sum(\hat{\hat{\beta}}^*_i - \hat{\hat{\beta}}_i)^2 + \sum(\bar{\bar{\beta}}^* - \hat{\hat{\beta}}_i)^2 - 2\sum(\hat{\hat{\beta}}^*_i - \hat{\hat{\beta}}_i)(\bar{\bar{\beta}}^* - \hat{\hat{\beta}}_i)}.$$

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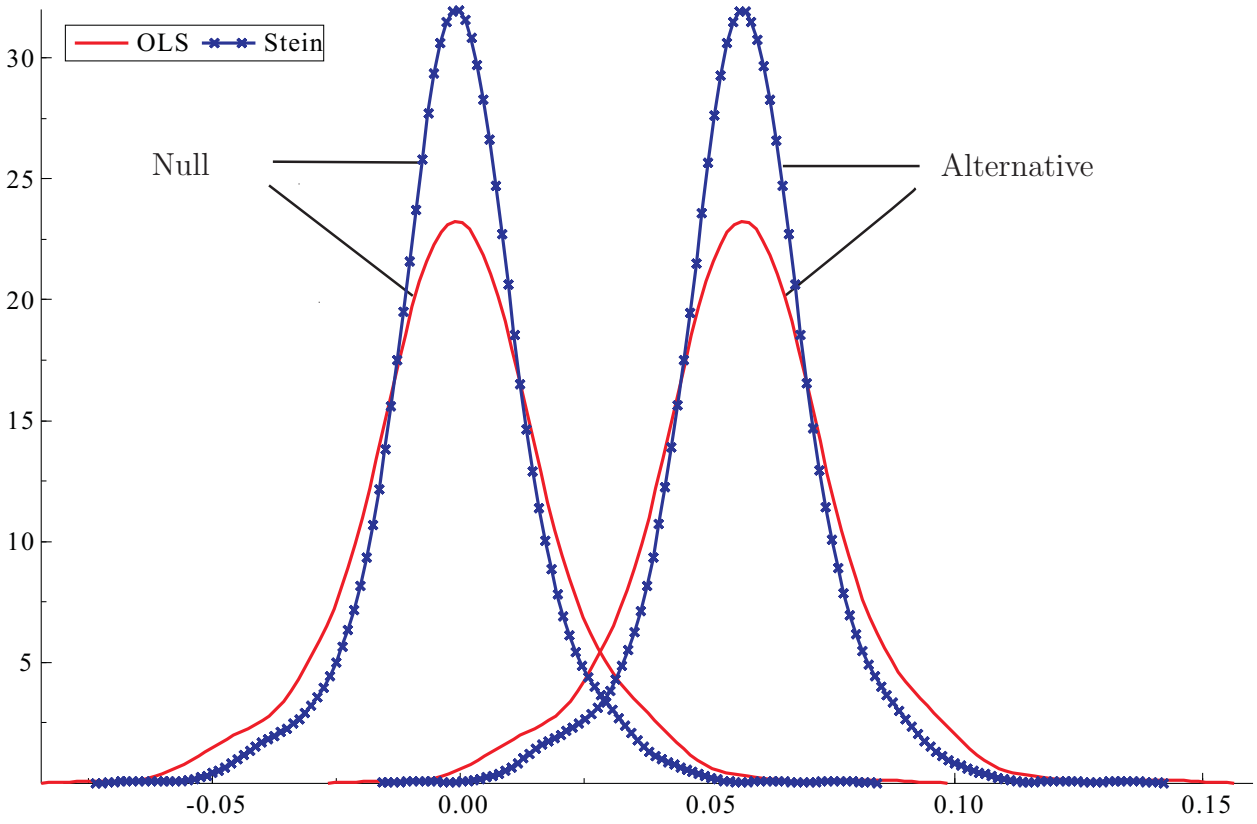

Figure 1: The small-sample distributions of the shrinkage and OLS Estimators under H_0 and H_a

Table 1: Relative estimation risk (Shrinkage/LS)

Country/Horizons	1		4		8		12		16	
	H_0 [b]	H_a [c]	H_0	H_a	H_0	H_a	H_0	H_a	H_0	H_a
MSE:[a]										
Canada	0.829	0.830	0.817	0.822	0.801	0.836	0.817	0.857	0.848	0.865
Germany	0.667	0.669	0.718	0.722	0.672	0.754	0.687	0.774	0.695	0.827
Japan	0.621	0.624	0.701	0.774	0.655	0.809	0.682	0.840	0.706	0.861
Switzerland	0.800	0.840	0.822	0.851	0.806	0.858	0.816	0.862	0.852	0.892
bias^2:										
Canada	0.875	0.763	0.422	1.209	0.912	1.502	0.733	1.423	1.236	1.201
Germany	0.626	0.891	0.963	1.104	0.802	0.825	0.832	0.861	1.153	1.424
Japan	1.632	1.230	0.870	1.429	0.637	1.410	0.816	1.520	0.822	1.535
Switzerland	1.422	1.229	1.352	1.341	0.403	0.854	0.534	0.732	0.833	0.778
variance:										
Canada	0.830	0.830	0.818	0.813	0.802	0.784	0.817	0.805	0.848	0.818
Germany	0.667	0.669	0.718	0.720	0.672	0.768	0.687	0.785	0.695	0.805
Japan	0.621	0.624	0.701	0.707	0.655	0.749	0.683	0.779	0.707	0.802
Switzerland	0.800	0.837	0.822	0.841	0.846	0.864	0.876	0.874	0.893	0.903

[a] MSE is defined as the sum of the bias squared and the variance of the parameter estimates:

$$\mathrm{MSE}(\tilde{\beta}_i) = \mathrm{E}\left[(\tilde{\beta}_i - \beta_i)^2\right] = \mathrm{E}\left\{\left[(\tilde{\beta}_i - \mathrm{E}(\tilde{\beta}_i)) + (\mathrm{E}(\tilde{\beta}_i) - \beta_i)\right]^2\right\} = \qquad \mathrm{variance}(\tilde{\beta}_i) + \mathrm{bias}(\tilde{\beta}_i)^2.$$

[b] The column gives the ratios of the MSE, bias squared, and variance of the Shrinkage estimates to by those of the OLS counterparts, under the null of no predictability.

[c] The column gives the ratios of the MSE, bias squared, and variance of the Shrinkage estimates to by those of the OLS counterparts, under the alternative of predictability.

Table 2: Power performance of the shrinkage estimator

(a) 5% significance level

Country/Horizons	1	4	8	12	16
Canada	0.845[a]	0.850	0.854	0.792	0.723
	(1.095)[b]	(1.108)	(1.131)	(1.145)	(1.172)
Germany	0.616	0.680	0.607	0.540	0.507
	(1.279)	(1.444)	(1.317)	(1.239)	(1.213)
Japan	0.826	0.778	0.863	0.807	0.760
	(1.309)	(1.319)	(1.214)	(1.171)	(1.193)
Switzerland	0.735	0.715	0.757	0.720	0.628
	(1.030)	(1.033)	(1.080)	(1.136)	(1.150)

(b) 10% significance level

Country/Horizons	1	4	8	12	16
Canada	0.925	0.941	0.925	0.868	0.790
	(1.085)	(1.079)	(1.087)	(1.081)	(1.078)
Germany	0.802	0.783	0.804	0.770	0.713
	(1.303)	(1.288)	(1.247)	(1.207)	(1.135)
Japan	0.912	0.896	0.920	0.907	0.847
	(1.078)	(1.106)	(1.108)	(1.106)	(1.107)
Switzerland	0.896	0.849	0.867	0.818	0.754
	(1.083)	(1.060)	(1.074)	(1.068)	(1.094)

[a] The entries represent size-adjusted power of the Shrinkage estimator against the alternative of exchange rate predictability.

[b] The entries in parentheses represent the power performance of the Shrinkage estimator relative to that of the OLS estimator (Shrinkage/OLS).

Table 3: Full-sample estimation results and tests for cointegration

statistics	$\tilde{\beta}_i$[a]	p-value[b]	R^2	p-value[c]	$\hat{\beta}_i$	$\bar{\beta}$	$\hat{\omega}_i$	std($\hat{\omega}_i$)[d]
Canada:								
1	0.035	**0.000**	0.035	**0.019**	0.029	0.052	0.772	0.311
4	0.131	**0.000**	0.104	**0.010**	0.106	0.207	0.734	0.285
8	0.285	**0.000**	0.218	**0.011**	0.237	0.428	0.727	0.289
12	0.370	**0.011**	0.194	**0.031**	0.230	0.625	0.742	0.314
16	0.379	**0.012**	0.133	**0.070**	0.291	0.790	0.813	0.342
Germany:								
1	0.051	**0.000**	0.036	**0.032**	0.045	0.052	0.125	0.340
4	0.195	**0.021**	0.119	**0.004**	0.178	0.207	0.183	0.295
8	0.412	**0.037**	0.214	**0.018**	0.385	0.428	-0.035	0.287
12	0.599	**0.042**	0.340	**0.013**	0.617	0.625	-0.047	0.320
16	0.767	**0.004**	0.483	**0.009**	0.832	0.790	0.083	0.346
Japan:								
1	0.051	**0.000**	0.037	**0.027**	0.049	0.052	0.100	0.328
4	0.199	**0.042**	0.121	**0.006**	0.207	0.207	0.008	0.301
8	0.408	**0.032**	0.229	**0.010**	0.454	0.428	-0.067	0.310
12	0.586	**0.062**	0.311	**0.012**	0.717	0.625	-0.111	0.324
16	0.734	**0.006**	0.376	**0.019**	0.947	0.790	-0.145	0.347
Switzerland:								
1	0.072	**0.000**	0.064	**0.000**	0.087	0.052	0.578	0.305
4	0.275	**0.000**	0.221	**0.000**	0.336	0.207	0.557	0.321
8	0.542	**0.000**	0.366	**0.001**	0.634	0.428	0.589	0.301
12	0.787	**0.000**	0.520	**0.000**	0.874	0.625	0.684	0.305
16	1.048	**0.001**	0.722	**0.000**	1.090	0.790	0.874	0.320

[a] Shrinkage estimates is defined as $\tilde{\beta}_i = \hat{\omega}_i\hat{\beta}_i + (1-\hat{\omega}_i)\bar{\beta}$, where $\hat{\beta}_i$ is the OLS estimate of the slope and the $\bar{\beta}$ is the grand average of the OLS estimates of the slopes of the 4 countries; $\hat{\omega}_i$ is the estimated optimal weight.

[b,c] P-value under the null of no exchange rate predictability ($\tilde{\beta}_i$=0 and R^2=0, respectively). Bold-faced numbers refer to p-values less than 10%.

[d] Standard deviation of the optimal weight estimates ($\hat{\omega}_i$).

Table 4: Out-of-Sample forecast evaluations: DM Statistic

Country	k	DM(A)[a]	p-value	p-value^{K}[c]	DM(20)[b]	p-value	p-value^{K}[d]
Canada	1	1.568	**0.015**	**0.041**	5.719	**0.000**	**0.027**
	4	1.500	**0.027**	**0.057**	1.786	**0.030**	**0.048**
	8	1.269	**0.065**	**0.015**	1.269	**0.070**	**0.016**
	12	-0.518	0.333	**0.064**	-0.523	0.319	**0.070**
	16	-1.378	0.655	0.110	-1.311	0.603	0.117
	max[e]	1.568	**0.052**	**0.060**	5.719	**0.005**	**0.056**
Germany	1	0.534	**0.095**	0.151	0.841	**0.093**	0.141
	4	0.438	0.144	0.162	0.529	0.139	0.160
	8	0.433	0.169	0.218	0.433	0.180	0.216
	12	0.627	0.186	0.249	0.603	0.196	0.250
	16	0.796	0.191	0.321	0.777	0.195	0.314
	max	0.796	0.288	0.273	0.841	0.300	0.268
Japan	1	0.770	**0.080**	**0.082**	0.990	**0.094**	0.104
	4	0.614	0.134	0.151	0.745	0.131	0.144
	8	0.855	0.129	0.133	0.890	0.136	0.133
	12	0.772	0.161	0.270	0.747	0.180	0.269
	16	0.729	0.170	0.451	0.717	0.180	0.433
	max	0.855	0.283	0.240	0.990	0.280	0.253
Germany	1	2.658	**0.003**	**0.010**	3.482	**0.003**	**0.023**
	4	2.586	**0.004**	**0.019**	2.718	**0.009**	**0.024**
	8	1.997	**0.033**	**0.045**	2.599	**0.018**	**0.039**
	12	1.744	**0.045**	**0.063**	1.981	**0.034**	**0.064**
	16	1.447	**0.063**	**0.077**	1.482	**0.080**	**0.097**
	max	2.658	**0.038**	**0.091**	3.482	**0.021**	**0.089**

Notes: The DM statistic is defined as $DM = \bar{d}/\sqrt{2\pi \hat{f}_d(0)/N_f}$, where $\bar{d} = N_f^{-1} \sum_{t=t_0+k}^{T} (u_{r,t}^2 - u_{m,t}^2)$ with $u_{r,t}$ and $u_{m,t}$ refer to the forecast errors of the random walk model and the monetary model, respectively. N_f is the number of recursive forecasts, and t_0 is the first date of forecast. $f_d(0)$ is the spectral density of $(u_{m,t}^2 - u_{r,t}^2)$ evaluated at frequency 0. Its consistent estimate $\hat{f}_d(0)$ is obtained using Newey and West (1987).

[a] DM statistic computed with truncation lags under Bartlett window set to 20.

[b] DM statistic with truncation lags under Bartlett window set by Andrews's (1991) algorithm.

[c,d] The corresponding p-value in Kilian (1999). Bold-faced numbers are those significant at 10% level.

[e] Joint test statistic proposed by Mark (1995), taking the maximum of a sequence of DM statistics indexed by k.

Table 5: Out-of-sample forecast evaluations: Theil's U

Country	k	Theil's U	p-value	p-value$^{K\,a}$
Canada	1	0.971	**0.009**	**0.042**
	4	0.936	**0.030**	**0.068**
	8	0.900	**0.043**	**0.057**
	12	1.063	0.549	**0.094**
	16	1.179	0.761	0.151
	min[b]	0.900	**0.081**	0.137
Germany	1	0.989	**0.061**	0.150
	4	0.979	**0.097**	0.169
	8	0.961	0.109	0.218
	12	0.864	**0.044**	0.291
	16	0.729	**0.010**	0.473
	min	0.729	**0.013**	0.283
Japan	1	0.987	**0.041**	0.118
	4	0.968	**0.090**	0.157
	8	0.927	**0.069**	0.145
	12	0.886	**0.051**	0.274
	16	0.838	**0.045**	0.534
	min	0.838	**0.053**	0.250
Swizerland	1	0.973	**0.006**	**0.017**
	4	0.929	**0.021**	**0.029**
	8	0.873	**0.025**	**0.045**
	12	0.808	**0.015**	**0.030**
	16	0.696	**0.000**	**0.026**
	min	0.696	**0.003**	**0.031**

Notes: Theil's U-statistic is defined as the ratio of the root-mean-square prediction error of the monetary model based on the shrinkage estimator to that of the random walk model. The null hypothesis is that the two models provide forecasts of equal accuracy (U=1). The alternative hypothesis is that the monetary fundamentals is more accurate (U<1).

[a] The corresponding p-values in Kilian (1999). Bold-faced numbers are those significant at 10% level.

[b] Joint test statistic according to Mark (1995), which takes the minimun of a sequence of Theil's U statistics indexed by k.

出席國際學術會議心得報告

計畫編號	95-2752-H-004-002-PAE
計畫名稱	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(1/4)
出國人員姓名 服務機關及職稱	郭炳伸 政治大學國貿系
會議時間地點	2006.12.11~12.12, Cass Business School, City University of London, London, UK
會議名稱	Breaks and Persistence in Econometrics
發表論文題目	Doing Justice to Fundamentals in Exchange Rate Forecasting

一、參加會議經過

會議的主辦單位是倫敦市立大學(City University, London)的 Cass Business School。該學院在商學管理專業碩士學程上享有非常高的知名度。該學院由於近倫敦金融中心，以財務、保險相關系所更為著稱。這些學科皆需高度資料分析，因此相對地計量分析在此自有其份量。

會議進行兩天(12 月 11 日與 12 日)，只有單一場次。因此所有人皆在同一研討會出入，氣氛十分熟絡融洽。大會從一百多篇投稿論文中，選擇了約二十篇宣讀，再加上六位受邀資深研究學者，共有二十六篇論文發表。其中約有一半以上的發表論文具有刊登於優良國際期刊的水準，是一個非常高水準的小型專業會議。

二、與會心得

這個會議的主題有關結構性變化與高度持續性的計量估計或處理。這二個主題其實都是傳統計量文獻一直在討論的議題，但最近的文獻似乎又有重新關注這兩個議題的趨勢。其原因在於追蹤資料以及更長的時間數列的持續累積，估計與檢測資料中的結構性變化與持續性似乎更比以前可能與迫切。這次會議有幾篇宣讀的論文在前述兩個主題上有非常重要的理論結果發表。首先，在追蹤資料下，偵測出未知結構變化時間點的估計已被證明可行。在單一時間數列下，欲估計出未知結構變化點，事實上並不可行。在追蹤資料下，由於有更多來自橫斷面的時間數列可用以估計，因此結構性變動時間點基本上已可辨認(identifiable)，而非呈現單一時間數列環境之離散分配現象。當然，即使有來自橫斷面的訊息，若變動點的變異過於龐大，仍然有可能無法順利辨認該結構變化點。因此在不同結構變動變異的假設下，變動時間點有著不同的收斂性質。其次，在追蹤資料下，建立檢測結構變動的檢定亦是可行。另外一系列的發表文獻分別探討各橫斷面有共同或單獨的結構性變動檢定。很多新建立的檢定其實都是過去單一時間數列下結構性變動檢定在追蹤資料下的延伸。在觀念上，這些新檢定並不難理解，但是在漸近性質推導上都是相當複雜的。這是因為推導過程需要同時兼顧時間長度與橫斷面數目的增加，自有其複雜性。

三、建議

這是一個小型但是過程相當緊湊的會議。在整個參加過程中，更由於任一時段只有單一場次，使得所有參加人員皆集中聆聽。身為一個參加者暨發表人，過程中享受到意見交換與腦力激盪的學術共鳴。除此之外，我相信這次成功的會議也部份歸因於許多資深學者的參與與發表論文，這當中的確有許多元素構成一次成功的研討會。國內舉辦的研討會也不在少數。在將來，如何組合這些元素，規劃會議，這次參加的經驗足以借鏡。

四、攜回資料名稱與內容

議程與論文簡介。

出席國際學術會議心得報告

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計畫名稱	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(1/4)
出國人員姓名 服務機關及職稱	郭炳伸 政治大學國貿系
會議時間地點	2006.12.15~12.16, Rotterdam, Netherlands
會議名稱	EC^2 meeting: The Econometrics of Monetary Policy and Financial Decision-Making
發表論文題目	Nonlinear Inflation Risk: Toward Resolving the Forward Premium Anomaly

一、參加會議經過

EC^2會議是歐洲計量學界由來已久且頗負盛名的會議。今年是第十七屆，在荷蘭鹿特丹於十二月十五日與十六日舉行。主辦單位是計量領域學術重鎮鹿特丹大學。以荷蘭人做事有條不紊的個性，整個會議過程流暢，各發表論文皆有相當水準。這些論文其實是從一百六十多篇投稿中選擇而出，競爭程度不可謂不激烈。更有特色的是，主辦單位所邀請的演講者皆是全美一流大學在貨幣計量領域的學者，充分展現主辦單位的號召力與學術關係。

二、與會心得

這次會議的主軸是財務與貨幣的相關計量研究。由於貨幣與財務研究側重於時間數列之應用，因此在會議中幾乎看不到有關個體計量的研究論文發表。但是卻有許多論文一致地以應用橫斷面的情報來改善或強化估計或檢定的結果。這與計量領域中許多研究集中於追蹤資料之趨勢是一樣的，可見貨幣或財務與計量兩個領域相互影響之深。因此，有部份學者，尤其是應邀而來的資深學者之發表論文有應用其他橫斷面總體數列所形成之 dynamic factors，以改善 DSGE (dynamic stochastic general equilibrium)模型參數估計；也有特別以利率結構(term structure)於新凱因斯模型之估計。另一論文發表主軸關乎模型不確定。理論模型只是對現實社會的近似，但是現實經濟的運作是不如理論模型描述一般簡化。因此當計量經濟學家以資料配適理論模型時，或經濟個體思慮經濟是否真如理論模型運作時，都將產生模型不確定性或模型錯誤設定。如何解決這些問題呢？這次會議中很多論文皆針對該問題提出看法或解決方案。歸納這些論文觀點，大概不外以 maxmin 或 Bayesian 兩種途徑提出方向。前者就是以「最壞打算」的思維進行分析，而後者則是在眾模型中取其平均。無論是哪一種分析方法，其實都是在避免極端情況發生，也都需要高度複雜的計算才可以獲得分析結果。無疑地，將來的經濟分析看來只會更量化，但更貼切實際。這樣的研究趨勢也與我的研究主題契合。目前我的研究有一大部分在於收縮估計式(shrinkage estimator)。該估計式其實具有平均的概念，但也具有結合橫斷面訊息的好處。在這次會議中，尚未發現有任何論文以收縮估計式進行分析。

三、建議

這次會議由於投稿者多，為了避免遺珠之憾，大會特別錄選若干論文以海報方式發表。這當中有很多品質很高的論文是來自年輕的歐洲博士班學生。這也意味歐洲的博士班訓練已與北美不分軒至。這種以海報方式進行作者與讀者的面對面溝通，對未踏出校門的博士生是成本低且有效率的最好訓練，似乎值得國內研討會借鏡。

四、攜回資料名稱與內容

議程。