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Forecasting on Dynamic Panel Regression with Cross Section Dependency - Asian Countries and Simulation Results

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Abstract

This paper studies the effects of the informative cross-section dependence on the dynamic panel regression estimation for Asia currencies in August, 2004 to August, 2007 and then compares forecasting performance for both daily and weekly returns. Traditional parametric approaches are Ordinary Least Squares (OLS), Seemingly Unrelated Regressions (SUR), Fixed Effects (FE) and Random Effects (RE) models. Nonparametric Random Effects panel data models are the Local Polynomial Least Squares (LPLS) and Local Polynomial Weighted Least Squares (LPWLS) estimators with cross-validation bandwidth.

The results show that the nonparametric LPLS could outperform the other models to forecast the daily returns. But there is inconclusive evidence to justify which model is the best to forecast the weekly returns. However, in general, the SUR could yields better results than the other models for weekly returns forecasting. This is according to the higher correlations among the estimated disturbances gathered from their individual AR(1) estimation. The results from the dynamic panel processes simulation are consistent with the returns forecasting outcomes.

Keywords: dynamic panel data model, fixed effects, nonparametric local estimator random effects.

1. Introduction

Economists have weak ability to explain the exchange rate movements as revealed by extensive studies focused on the major industrial countries. The popular structural models could not outperform a naïve random-walk model over horizons of twelve month or less, even in predicting the realized values of the exogenous explanatory variables. See Meese and Rogoff [25].

However, exchange rates were found by Ito et al. [19] to have impacts on trade and investment for almost countries in Asia region except the fast growing economies. Mckenzie [24] studied the effects of exchange rate volatility on trade and could identify the reasoning to form currency union in the East Asian region. And also, in economic linkage perspective, Han and Hoontrakul [12] measured the stock market co-movements by testing the cointegration analysis and could found the contagion effect in South East Asia both prior and after the crisis in 1997. Accordingly, Chaisrithong [6] examined Thai exchange rate between 1997 and 2002 by using Vector Autoregressive (VAR) and revealed that contagion effect have more contribution in explaining the Thai nominal exchange rate fluctuation than fundamental effects.

Thus, the inter-correlation among the exchange rates in Asia region may exhibit more ability to explain fluctuation of exchange rates. So this study will consider the time-series econometric models on the forecasting performance of exchange rates in Asia region. The dynamic panel data models will forecast exchange rate returns with considered whether the information of cross relation among returns could increase the ability to explaining the co-movement of exchange rates.

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2. Theoretical Framework and Methodology

The pooling of observations on a cross-section of the interesting units is determined to explain changes and effects on the empirical phenomena. The main literature in this area usually assumes a specific parametric linear form. In contrast to this approach, this study applies an unspecified nonparametric relationship over time for a group of individual and compares the prediction performance comparison among the alternative panel data models.

An important question arises for the panel data on this issue is the poolability of data. See Baltagi et al. [4] for discussion on this issue. In Hoogstrate et al. [18], the empirical results for 18 Organization for Economics Corporation and Development (OECD) countries parametrically analyzed effects from pooling in dynamic panel data forecasts and found that Generalized Least Squares (GLS) pooled forecasts outperformed Ordinary Least Squares (OLS) pooled, GLS individuals and OLS individuals. Jithitikulchai [22] extended the forecasting comparison by proposed the nonparametric approach. He found that, generally, the results of forecasting performance comparison show that pooled data is better than not pooled and can find grounds for choosing nonparametric models by the comparison with parametric models.

In this study, we also apply the models with pool and not pool data for both the parametric and nonparametric approaches.

I. The Parametric Models

1.1) Individual Ordinary Least Squares (OLS)

We first consider the basic model, $y_i = \alpha + \beta x_i + u_i \quad ; i = 1,...,N$ where $u_i \sim N(0, \sigma_{u_i}^2)$. Suppose that all the classical assumptions of Gauss-Markov theorem are satisfied for all $i = 1,...,N$ and thus the OLS estimators of α and β obtain the Best Linear Unbiased Estimator (BLUE) properties.

However, there are possibilities that the correlated disturbances in separated OLS equations can provide useful information for more accuracy in pooled estimation. This system of equations is called Seemingly Unrelated Regressions in which the datasets are not pooled (SUR – Not Pooled),

$$\begin{pmatrix} y_1 \\ \vdots \\ y_N \end{pmatrix} = \alpha + \begin{pmatrix} x_1 & & 0 \\ & \ddots & \\ 0 & & x_N \end{pmatrix} \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_N \end{bmatrix} + \begin{pmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_N \end{pmatrix}.$$

And the variance-covariance matrix is in the form of $\Sigma \otimes I_T$ where $\Sigma = \left[\sigma_{ij}\right]$, $\sigma_{ij} = u_i{'}u_j/(T-2) \; ; i = 1,...,N, \; j = 1,...N$, $\otimes$ denotes the Kronecker product and T denotes the periods of this balanced panel.

For $i = 1,...,N$; the estimators of u_i from the individual OLS regression estimation are therefore computed for the SUR variance-covariance matrix. Baltagi [2] has the compact presentation of both intuitive and theoretical view on SUR. See full details in Greene [9] and Wooldridge [34].

The SUR models in this study will have two functional forms which have *with* and *without* interception. The estimation technique is Feasible Generalized Least

Squares (FGLS). Therefore we have three models. One is the individual OLS model and two are SUR.

1.2) Pooled Ordinary Least Squares (OLS)

In this case, the individual units are combined to be one sample,

$$\begin{pmatrix} y_1 \\ \vdots \\ y_N \end{pmatrix} = \alpha + \begin{pmatrix} x_1 \\ \vdots \\ x_N \end{pmatrix} \beta + \begin{pmatrix} u_1 \\ \vdots \\ u_N \end{pmatrix}$$

with $u \sim N(0, \sigma_u^2)$ where $u = \begin{bmatrix} u_1 & \cdots & u_N \end{bmatrix}'$

Given the classical assumptions of regression, we also have the Pooled Seemingly Unrelated Regressions models (SUR – Pooled) *with* and *without* interception as same as the above Individual OLS model. But the difference is that the disturbances for compute the variance-covariance matrix $\Sigma \otimes \mathrm{I}_T$ comes from the Pooled OLS estimation of all concatenated series where $\Sigma = \left[\sigma_{ij} \right]$, $\sigma_{ij} = u_i ' u_j /(T-2)$; $i = 1,..., N,\ j = 1,...N$.

1.3) Panel Data Models

Economists apply application of panel data models to study the cross-sectional units observed over time. Modern empirical research that can be fitted to cover more data configurations including space and time dimensions of panel data model, i.e. on estimation and forecasting applications, are increasing by demands for understand and interpret the real phenomena. The examples of dynamic panel on empirical application can be found in Garcia [7] on elaticities of energy demand and Garin [8] on inbound international tourism. Baltagi [3] provided the coverage of panel data estimation and testing techniques for various topics in econometrics including dynamic panel data models and nonstationary panel. Hansen [13] considered a robust covariance matrix estimator which is a generalization of the traditional heteroskedasticity consistent estimator for panel data model. His estimator allows arbitrary correlation within each individual. He gave the analytical results of estimator and its tests for many cases of asymptotically convergence of N and T.

However, theoretically for estimation purpose, the traditional parametric estimators of dynamic panel data model have limitation on unbiasedness especially when the parameters are heterogeneous across countries and the regressors are serially correlated. But consistency could gained from $T \to \infty$, see Baltagi [3]. Hansen [14] considered fixed effects panel with autocorrelation and offered the bias-correction implementation for the parameters of the autoregressive process. The usefulness of his FGLS and the derived bias-correction was illustrated by removes a substantial portion of the bias from the AR parameter estimates.

1.3.1 Fixed Effects (FE) Estimator

The basic panel regression model considered here has the form, $y_{it} = \alpha + \beta x_{it} + \mu_i + \nu_{it} \;\; ; i = 1, ..., N \;\; t = 1, ..., T$. The μ_i , individual effect or unobserved heterogeneity, are assumed to be fixed parameters in this case to be estimated. And the remainder idiosyncratic disturbances ν_{it} are stochastic with $\nu_{it} \sim iid(0, \sigma_\nu^2)$, the independent and identical distributed disturbances. The x_{it} are assumed independent of the ν_{it} for all i and t. Technically, the estimation technique will use Least Square Dummy Variables (LSDV) to obtain the estimators. See details in Baltagi [3].

For dynamic panel data model with fixed effects, Hahn and Kuersteiner [11] developed an estimator, robust to stationarity, be removed asymptotic bias due to the well-known incidental parameter problem; the inconsistency of the MLE of the localizing-to-unity parameter in the heterogeneous trend of dynamic panel regression model. See the asymptotic properties of the Gaussian maximum likelihood estimators of both the homogeneous and heterogeneous deterministic trends in Moon and Phillips [26].

And an interesting matter of course was derived by Phillips and Sul [31] which they extended from the efforts on bias reduction and cross-section dependency removing in Phillips and Sul [30]. Phillips and Sul [31] proved that although the cross section sample size $N \to \infty$, when there is cross-section error dependence, the probability limit of the dynamic panel regression estimator is a random variable rather than a constant even when N is large.

1.3.2 Random Effects (RE) Estimator

Since there are too many parameters in the fixed effects model and the loss of degrees of freedom occurred, thus we can avoid these by assume that μ_i are random. Then the model is

$$y_{it} = \alpha + \beta x_{it} + \mu_i + v_{it} \; ; i = 1,...,N \;\; t = 1,...,T \text{ , where } \mu_i \sim iid(0, \sigma_\mu^2) \text{ ,}$$

$v_{it} \sim iid(0, \sigma_v^2)$, and the μ_i are independent of v_{it} . In addition, the x_{it} are independent of the μ_i and v_{it} , for all i and t .

Then, for estimation and inference objective, one can find the variance-covariance matrix, $\Omega = E(uu') \; = \sigma_\mu^2 (I_N \otimes J_T) + \sigma_v^2 (I_N \otimes I_T)$, where J_T is a matrix of ones of dimension TxT . In fact, $\text{cov}(u_{it}, u_{js}) \; = \sigma_\mu^2 + \sigma_v^2$ for $i = j, \; t = s$, and $\text{cov}(u_{it}, u_{js}) \; = \sigma_\mu^2$ for $i = j, \; t \neq s$, and zero otherwise. This implies a homoskedastic variance $\text{var}(u_{it}) = \sigma_\mu^2 + \sigma_v^2$ for all i and t , and an equicorrelated block-diagonal covariance matrix which exhibits serial correlation over time only between the disturbances of the same individual. See discussion on the estimation of consistent estimators of the variance component with spectral decomposition in Baltagi [3]. See also semiparametric efficient estimation of AR(1) of random effects panel data models in Park, Sickles, and Simar [28], [29].

II. The Nonparametric Models

Parametric method is statistically simple and if the assumptions of a parametric model are justified, the regression function can be estimated more efficiently than it can be done by a nonparametric method. Jithitikulchai [21]'s comparative forecasting results for univariate data generating processes showed that the classical OLS perform the best among other forecasts for the simulated simple linear model with standard normal disturbances, but the nonparametric model could gain forecasting advantage, especially in high fluctuated processes with violation of OLS classical assumptions. Moreover, many assumptions are made in coming up with the questions about the functional relations and the distributional features of variables, especially in the empirical researches.

On the other way, the nonparametric approach is preferred because the minimum of structure imposed on the regression function. It is only necessary that the regression function satisfies some degree of smoothness. Typically, continuity of function is enough to ensure the convergence of estimator as the size of data increases. Additional existence of derivatives, degree of smoothness, allows more efficient asymptotically. See Jithitikulchai [20] for the introductory nonparametric econometrics on the cross-validation bandwidth and local linear estimator. The intuitive concept of nonparametric econometrics and the simulated illustration of different bandwidths and some kinds of local estimators were provided.

2.1) Nonparametric Local Polynomial Least Squares Estimator

The basic framework is the following model duplicated from Henderson and Ullah [17]: $y_{it} = m(x_{it}) + \varepsilon_{it}$ for $i = 1,...,N$ and $t = 1,...,T$, where $m(.)$ is an unknown smoothing function of the conditional mean.

Furthermore, ε_{it} follows the random effects specification $\varepsilon_{it} = \mu_i + \nu_{it}$ where $\mu_i \sim iid(0,\sigma_\mu^2)$, $\nu_{it} \sim iid(0,\sigma_\nu^2)$ and the μ_i are independent of ν_{it} . And the covariance matrix for the full $NT \times 1$ disturbance vector ε is defined as in the above parametric random effect model. Please note that this study use Gaussian kernel function, optimal cross-validation bandwidth, and local polynomial degree two estimators.

2.2) Nonparametric Local Polynomial Weighted Least Squares Estimator

Nonparametric kernel estimation in this study can be obtained from local polynomial estimator with the second polynomial degree which is greater than first polynomial degree of local linear least squares (LLLS) estimator in Henderson and Ullah [17]. By minimizing the local least squares of errors, $\sum_i \sum_t (y_{it} - X_{it}\delta(x))^2 K(x_{it} - x/h) \quad = (Y - X\delta(x))' K(x)(Y - X\delta(x))$ with respect to $\delta(x)$, where X_{it} is $(1,(x_{it}-x),(x_{it}-x)^2/2)$, $K(x)$ is an $NT \times NT$ diagonal matrix of kernel functions $K(x_{it} - x/h)$ and h is the optimal cross-validation bandwidth (smoothing) parameter. But the LLLS estimator in Henderson and Ullah [17] use $X_{it} = (1,(x_{it} - x))$. Our obtained estimator is in the form of GLS as: $\hat{\delta}(x)$ $= (X'K(x)X)^{-1} X'K(x)y$.

And the numerical process to find the optimal “leave-one-unit-out” smoothing bandwidth will delete all the T observations in time dimension of the i^{th} unit as in Henderson and Simar [16]. See also in Hahn and Kuersteiner [11] on studying the bandwidth selection for spectral density estimators based on dynamic nonlinear panel data models.

Nevertheless, Henderson and Ullah [17] pointed out that LLLS estimator ignores the information contained in the disturbance vector covariance matrix Ω. So they introduced the feasible three alternative estimators, which have the generalized form of kernel weighted: $d_r(x) = (X'W_r(x)X)^{-1}X'W_r(x)y$; for $r = 1, 2, 3$, where $W_1(x) = \sqrt{K(x)}\Omega^{-1}\sqrt{K(x)}$, $W_2(x) = \Omega^{-1}K(x)$, and $W_3(x) = \Omega^{-1/2}K(x)\Omega^{-1/2}$, so called Local Linear Weighted Least Squares (LLWLS) estimators. Depends upon the unknown parameters σ_μ^2 and σ_ν^2, the spectral decomposition of Ω leads to consistent estimators of variance components. See Baltagi [3] for analysis on this spectral decomposition. Furthermore, the consistency properties of these estimators were discussed in Henderson and Ullah [17].

Methodology on Forecasting Performance

The forecasting performance measure for dynamic regression models is the rolling mean absolute prediction error [1]. The rolling algorithm uses the updating observations to forecast the next realization, i.e. use the first T observations to forecast the $\hat{y}_{T+1}$, and updating by one observation to use the second T observations started by the 2^{nd} observation until the $(T+1)^{th}$ to forecast the $\hat{y}_{T+2}$, and so on, for each additional round of iteration until the last round of forecasting. Then we can have the mean absolute prediction error which is $\sum_{j=1}^{J}\left|y_{t+j} - \hat{y}_{t+j}\right| / J$ for each rolling observation set.

3. Simulation Results

This section will study the forecasting comparison among the proposed models for the simulated data generating processes. Some examples of linear trends are studied with their main differences on various characteristics of disturbances for each trend processes. Almost all of the generated time trends have the similar mean equations.

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[1] This criterion is similar to the Mean Squared Prediction Error (MSPE) concept. However, this is not the same as the Mean Absolute Percentage Error (MAPE).

However, although the compartment model, as in Budsaba [5], has the idiosyncratic mean equations; but they have the same standard normal disturbances. And in this section we will use the average of rolling mean absolute prediction error to compare the forecasting performance among the proposed econometric models. Different combinations of N units and T times could gain in the increasing in accuracy of the forecasting comparison results.

Table 1. Average Rolling Mean Absolute Prediction Error of Linear Trend with Normal Disturbances

$y_{i,t} = 1.5 + .01t + u_{i,t} \quad ; u_{i,t} \sim N(0, .25)$

T	N	Individual			Pool			Panel Model		Nonparametric Model	
		OLS	SUR1	SUR2	Pool OLS	SUR1	SUR2	FE	RE	LPLS	LPWLS
5	12	0.2897	0.9604	1.2784	0.2960	0.4916	0.6785	0.3432	0.3012	0.3800	0.4600
10	12	0.3258	1.4411	7.2938	0.3427	272.7884	0.5231	0.3924	0.3455	0.3872	0.3916
20	12	0.4030	3.9660	3.0903	0.3860	1.9274	0.5003	0.4331	0.3851	0.4611	1.1873
5	20	0.2872	0.4018	0.8849	0.2713	0.3887	0.7963	0.2917	0.2727	0.2719	0.3280
10	20	0.3749	0.6180	0.7280	0.3361	0.4352	0.5384	0.3633	0.3347	0.3200	0.3699
20	20	0.4255	38.9324	5.8956	0.3943	1.2647	0.5034	0.4276	0.3956	0.4125	0.4829
5	30	0.3748	0.4813	0.8716	0.3419	0.4796	0.8795	0.3370	0.3399	0.4254	0.4006
10	30	0.4197	0.5468	0.5987	0.3818	0.5453	0.5944	0.3730	0.3837	0.4124	1.2652
20	30	0.4364	6.6799	1.4906	0.3918	0.5492	0.4981	0.3974	0.3924	0.3959	0.4390

The results of prediction performance comparison for linear trend process with normal disturbance are illustrated in Table 1 above. We can see that the pool OLS model is the best result from the most occurrence of minimal average of rolling mean absolute prediction error for all units in each of the cases on studying. This result could be anticipated by the homogeneous linear trend with small variation in normal disturbances. So the pooled data could gain the accuracy by increase in the observation sizes.

Table 2. Average Rolling Mean Absolute Prediction Error of ARCH

$y_{i,t} = .1 + .01t + u_{i,t}$

where $u_{i,t} = s_{i,t} v_{i,t} \; ; v_{i,t} \sim iid(0,1)$ with $s_{i,t}^2 = E(u_{i,t}^2) = .05 + .5u_{i,t-1}^2$

T	N	Individual			Pool			Panel Model		Nonparametric Model	
		OLS	SUR1	SUR2	Pool OLS	SUR1	SUR2	FE	RE	LPLS	LPWLS
5	12	0.2044	0.2415	0.2186	0.1314	0.2137	0.1561	0.1680	0.1253	0.1409	0.1799
10	12	0.2366	0.4431	1.7874	0.2033	0.4256	0.2030	0.2289	0.1993	0.2025	0.2083
20	12	0.3567	1.1154	0.9254	0.2805	0.4415	0.2815	0.3056	0.2789	1.0861	0.3562
5	20	0.1817	0.2499	0.1816	0.1671	0.2394	0.1694	0.1797	0.1669	0.1684	0.2056
10	20	0.2182	0.2748	0.2343	0.2170	0.2675	0.2191	0.2412	0.2168	0.2171	0.2135
20	20	0.2373	2.9979	21.7907	0.2447	0.5548	0.2417	0.2600	0.2432	0.2476	0.2510
5	30	0.2715	0.2894	0.2713	0.2610	0.2894	0.2725	0.2630	0.2607	2.6373	2.5950
10	30	0.3089	0.3769	0.2877	0.2688	0.3658	0.2792	0.2704	0.2695	0.9141	0.4819
20	30	0.2885	1.7385	0.3717	0.2640	0.3562	0.2684	0.2600	0.2641	0.2672	0.2989

The simulated homogeneous linear trends with Autoregressive Conditional Heteroskedasticity (ARCH) disturbances in Table 2 have the traditional parametric random effect model to be the best model to forecast the simulated observations.

The results are quite clear on the distinguished performance of the random effect model. Therefore, introduces the random effect estimators to the panel model when there are ARCH effects in the individual series could yield in accuracy of forecasting the realizations.

In Table 3, the simulated homogeneous linear trends with Generalized ARCH (GARCH) disturbances in Table 3 have different numbers of N units and T times with satisfied covariance stationary constraint.

Table 3. Average Rolling Mean Absolute Prediction Error of GARCH

$y_{i,t} = .05 + .005t + u_{i,t}$

where $u_{i,t} = s_{i,t} v_{i,t}\ ; v_{i,t} \sim iid(0,1)$ with $s_{i,t}^2 = E(u_{i,t}^2) = .1 + .4u_{i,t-1}^2 + .4s_{i,t-1}^2$

T	N	Individual			Pool			Panel Model		Nonparametric Model	
		OLS	SUR1	SUR2	Pool OLS	SUR1	SUR2	FE	RE	LPLS	LPWLS
5	12	0.7254	0.9791	1.4185	<u>0.7167</u>	0.9636	1.6046	0.8352	0.7249	0.7438	0.7635
10	12	0.9545	5.4206	12.7146	0.8037	4.5558	1.1598	0.8031	0.8037	<u>0.7916</u>	0.8228
20	12	0.8234	10.4134	2.2961	0.6662	3.1710	0.8107	0.7117	<u>0.6626</u>	0.6864	1.0345
5	20	0.3890	0.6166	1.0524	0.3952	0.5401	1.1018	0.4652	0.3943	<u>0.3587</u>	0.3621
10	20	0.5925	1.1887	1.3778	0.5257	0.8139	1.0045	0.5698	<u>0.5239</u>	0.5572	0.6755
20	20	0.5488	20.1120	5.2915	0.4935	6.5433	0.6947	0.5209	0.4912	<u>0.4867</u>	0.5924
5	30	0.6496	0.7593	1.3143	0.6320	0.7238	1.3797	0.6264	0.6229	0.6881	<u>0.5943</u>
10	30	0.6273	0.8136	1.0760	0.6419	0.7690	1.1987	0.6393	0.6364	<u>0.6216</u>	0.7165
20	30	0.6051	9.0114	1.3515	0.6094	1.1437	0.8627	0.6104	0.6006	<u>0.5795</u>	0.8225

However, the simulated processes have their roots of lag polynomials very close to the circumference of unit circle. Therefore, unsurprisingly, we have the nonparametric local polynomial least squared model to be the best model to forecast the simulated process.

Table 4. Average Rolling Mean Absolute Prediction Error of Autoregressive Disturbances

$y_{i,t} = .5 + .01t + u_{i,t}$

where $u_{i,t} = a_i u_{i,t-1} + v_{i,t}$; $a_i \sim iid(0, 0.25)$, $v_{i,t} \sim iid(0,1)$

T	N	Individual			Pool			Panel Model		Nonparametric Model	
		OLS	SUR1	SUR2	Pool OLS	SUR1	SUR2	FE	RE	LPLS	LPWLS
5	12	0.8415	0.5836	0.9953	0.5107	0.5809	0.7669	0.8343	0.4883	0.5644	1.1925
10	12	0.9536	1.4254	1.3680	0.6913	0.7226	0.7578	1.0212	0.6818	0.6857	0.7021
20	12	1.0194	2.5839	2.1143	0.8266	2.0851	0.8465	1.2325	0.8411	0.8411	0.8204
5	20	0.6023	0.6752	0.9406	0.5496	0.6683	0.8545	0.7130	0.5587	0.6424	0.6190
10	20	0.7946	0.8897	1.0914	0.7523	0.8232	0.9634	1.1389	0.8029	0.8044	0.7953
20	20	0.7810	8.0328	18.4161	0.7762	1.4741	0.8317	1.1367	0.8256	0.8315	0.8989
5	30	0.9809	0.8349	0.8450	0.8415	0.8266	0.8254	0.8363	0.8430	1.2229	1.5318
10	30	0.9737	0.8916	0.8560	0.8138	0.8811	0.8327	0.8301	0.8240	0.8477	0.8238
20	30	0.9452	2.3738	0.9512	0.8123	0.8185	0.7950	0.8377	0.8189	0.8200	0.8190

The linear trend processes in Table 4, given that the disturbances with $i.i.d.$ autoregressive coefficients, show that the pool OLS is the best model to forecast the simulated realizations. The simulation forecasting results show that the pool OLS model has the distinction of having the maximum cases of minimal average of rolling mean absolute prediction error.

Table 5. Average Rolling Mean Absolute Prediction Error of Heteroskedasticity Disturbances

$y_{i,t} = .25 + .001t + \mu_i + u_{i,t}$

where $\mu_i \sim N(0, .0625)$ and $u_{i,t} \sim N(0,1)$

T	N	Individual			Pool			Panel Model		Nonparametric Model	
		OLS	SUR1	SUR2	Pool OLS	SUR1	SUR2	FE	RE	LPLS	LPWLS
5	12	1.3451	1.2400	8.5883	0.8766	1.0249	9.3704	1.3119	0.9141	0.9626	0.9546
10	12	1.4429	15.0413	48.3991	1.0112	9.4893	2.7738	1.9566	1.1834	1.0541	1.0525
20	12	1.5792	28.6271	78.2465	1.1843	15.5639	2.1487	2.1871	1.3858	1.2186	1.1825
5	20	1.1230	0.9004	5.4741	0.9221	0.8971	5.1579	1.0148	0.8706	1.0338	1.1671
10	20	1.3264	1.2414	1.6774	1.1326	1.2456	2.4083	1.3988	1.1246	1.2011	1.2328
20	20	1.4234	45.7519	39.3200	1.2133	7.8352	2.1465	1.5154	1.2342	1.2339	1.2137
5	30	1.0498	1.0670	3.8146	1.0175	1.0665	3.7988	1.0233	1.0127	1.0755	1.5205
10	30	1.2377	1.2220	2.1871	1.1491	1.2230	1.7954	1.1895	1.1399	1.3007	1.3508
20	30	1.2876	32.3410	5.1325	1.1553	1.2063	1.5773	1.2185	1.1488	1.2298	1.2770

As was analyzed in Baltagi [3], the disturbance series have heteroskedasticity property. And this peculiar series was included in linear trend data generating process. The random effect model is the best model measured by the maximum numbers of minimal average rolling mean absolute prediction error as illustrated in Table 5.

Table 6. Average Rolling Mean Absolute Prediction Error of Compartment Model

$$y_{i,t} = a_i(\exp(-b_i t) + \exp(-c_i t)) + u_{i,t}$$

where $a_i \sim N(0,.0025),\ b_i \sim N(0, 0.0625),\ c_i \sim N(0, 0.0625)$

and $u_{i,t} \sim N(0,1)$

T	N	Individual			Pool			Panel Model		Nonparametric Model	
		OLS	SUR1	SUR2	Pool OLS	SUR1	SUR2	FE	RE	LPLS	LPWLS
5	12	1.2883	1.2516	2.1041	1.1865	1.3420	1.2185	1.2706	1.3365	3.1486	3.3898
10	12	1.7803	5.3711	4.3570	1.6748	2.3665	1.6755	1.7923	1.7976	1.6064	2.4676
20	12	1.9859	5.3006	36.4722	1.5396	1.5790	1.5265	1.7306	1.5649	1.6736	12.7488
5	20	1.6540	1.8375	1.7360	1.6027	1.8136	1.6449	1.7219	1.5904	1.5243	1.6558
10	20	1.7270	1.8231	1.6634	1.6092	1.7600	1.6078	1.6612	1.6249	1.5815	2.9246
20	20	1.9143	4.4205	4.5749	1.7194	2.3004	1.7221	1.7552	1.7149	1.7050	2.1018
5	30	2.2978	2.1424	2.2506	2.1721	2.1261	2.2322	2.1385	2.1640	2.3380	2.8200
10	30	2.0801	1.9770	1.9888	1.9992	1.9780	2.0076	1.9915	1.9949	2.0630	2.6075
20	30	2.1023	6.4699	8.5935	1.9917	1.9804	2.0092	1.9608	2.0001	2.2264	3.3498

The data generating processes of the compartment time trends in Table 6 have idiosyncratic mean equations with homogeneous standard normal disturbances. See Compartment Models in Budsaba [5]. The ability of the nonparametric local polynomial least squares model is higher than the others to forecast the realization.

4. Empirical Results

We study the forecasting performance among the models for exchange rates against US dollar. Data are the returns of weekly and daily nominal exchange rates for some selected countries in Asia region for 2004:8 to 2007:8. There are China yuan (CNY), Indonesia rupiah (IDR), Japan yen (JPY), Korea won (JPY), Myanmar kyat (MYR), Philippines peso (PHP), Singapore dollar (SGD), and Thai baht (THB).

Augmented Dickey-Fuller test with deploying of constant and linear trend as exogenous variables does not detect unit root.

Table 7. Augmented Dickey-Fuller Unit Root Test on Daily Returns

	t-Statistic	one-sided p-values	Test critical values: 1% level	5% level
CNY	-33.9456	0.0000	-3.4361	-2.8640
IDR	-23.5641	0.0000	-3.4361	-2.8640
JPY	-30.2423	0.0000	-3.4361	-2.8640
KRW	-20.1244	0.0000	-3.4361	-2.8640
MYR	-23.6652	0.0000	-3.4361	-2.8640
PHP	-31.1088	0.0000	-3.4361	-2.8640
SGD	-25.5991	0.0000	-3.4361	-2.8640
THB	-28.8120	0.0000	-3.4361	-2.8640

Table 8. Augmented Dickey-Fuller Unit Root Test on Weekly Returns

	t-Statistic	one-sided p-values	Test critical values: 1% level	5% level
CNY	-19.1190	0.0000	-3.4517	-2.8708
IDR	-17.7296	0.0000	-3.4517	-2.8708
JPY	-16.0603	0.0000	-3.4517	-2.8708
KRW	-22.5437	0.0000	-3.4517	-2.8708
MYR	-19.2698	0.0000	-3.4517	-2.8708
PHP	-17.4202	0.0000	-3.4517	-2.8708
SGD	-15.1907	0.0000	-3.4517	-2.8708
THB	-15.6798	0.0000	-3.4517	-2.8708

1. Daily Returns

The forecasting performance comparison for daily returns of currencies will test four cases for different sizes of initial observations before rolling forecast to obtain the rolling mean absolute prediction error where T = 432.

Most of the linear relationship level among the countries is quite low, except for some cases such as the correlation between Singapore Dollar and Japan Yen or the correlation between Korea Won and Malaysia Ringgit.

Please note that Thailand Baht is comparatively high correlated with Singapore Dollar and Japan Yen. And the disturbances from their individual AR(1) without constant have the similar structure of correlation as their daily returns.

Table 9. Correlation Matrix of Daily Returns

	CNY	IDR	JPY	KRW	MYR	PHP	SGD	THB
CNY	1.0000	0.0247	0.0370	0.0928	0.0248	-0.0018	0.0233	0.0366
IDR	0.0247	1.0000	0.0972	0.0497	0.0586	0.1764	0.2386	0.0138
JPY	0.0370	0.0972	1.0000	0.1460	0.1277	0.0697	0.5840	0.2099
KRW	0.0928	0.0497	0.1460	1.0000	0.5932	0.2569	0.2123	0.0293
MYR	0.0248	0.0586	0.1277	0.5932	1.0000	0.1855	0.1175	-0.0282
PHP	-0.0018	0.1764	0.0697	0.2569	0.1855	1.0000	0.2972	0.1000
SGD	0.0233	0.2386	0.5840	0.2123	0.1175	0.2972	1.0000	0.2967
THB	0.0366	0.0138	0.2099	0.0293	-0.0282	0.1000	0.2967	1.0000

Table 10. Correlation Matrix of Disturbances from Individual AR(1)

	CNY	IDR	JPY	KRW	MYR	PHP	SGD	THB
CNY	1.0000	0.0236	0.0270	0.1037	0.0291	0.0087	0.0146	0.0435
IDR	0.0236	1.0000	0.0949	0.0713	0.0619	0.2184	0.2285	0.0065
JPY	0.0270	0.0949	1.0000	0.1600	0.1493	0.0871	0.5819	0.2025
KRW	0.1037	0.0713	0.1600	1.0000	0.5655	0.2483	0.2107	0.0338
MYR	0.0291	0.0619	0.1493	0.5655	1.0000	0.1902	0.1183	-0.0143
PHP	0.0087	0.2184	0.0871	0.2483	0.1902	1.0000	0.3111	0.0899
SGD	0.0146	0.2285	0.5819	0.2107	0.1183	0.3111	1.0000	0.2924
THB	0.0435	0.0065	0.2025	0.0338	-0.0143	0.0899	0.2924	1.0000

The nonparametric local polynomial least squares (LPLS) outperform the other models on forecast the daily returns. The underlined and italic rolling mean absolute prediction error is the minimum amount of error measurement among all models for each country. It is clear that if LPLS is the best for any country, then its rolling mean absolute prediction error is very small compared to the others. However, if it is not true that LPLS has minimum rolling mean absolute prediction error, then the rolling mean absolute prediction error of the best one will not much differ from the others.

Please also note that the local weighted least squares estimator (LWLS) will not be represented for all three alternative estimators as in Henderson and Ullah [17], since all of their forecasts, and thus the rolling mean absolute prediction error, are almost exactly the same. And the number of iterations for rolling forecasting equates to $T-T0$.

Table 11. Rolling Mean Absolute Prediction Error of Daily Returns

Initial T	Individual			Pool			Panel Model		Nonparametric Model	
Sample	OLS	SUR1	SUR2	Pool OLS	SUR1	SUR2	FE	RE	LPLS	LPWLS
T0=trunc(T.4)*										
CNY	0.0689	0.0676	0.0680	0.0707	*0.0675*	0.0677	0.0726	0.0706	0.1020	0.5259
IDR	0.3713	0.3530	*0.3314*	0.3741	0.3463	0.3392	0.3751	0.3732	0.3923	3.2903
JPY	0.2255	0.2185	0.2230	0.2470	0.2171	0.2238	0.2494	0.2468	*0.2114*	0.8329
KRW	0.9100	0.8759	0.9799	0.8748	0.8734	0.9180	0.8716	0.8737	*0.6987*	1.1538
MYR	0.9728	0.8983	0.8994	0.8952	0.8968	0.8960	0.9280	0.8939	*0.7230*	1.0859
PHP	0.2825	0.2972	0.2840	0.2824	0.2931	0.2833	0.3022	*0.2815*	0.3204	0.7281
SGD	0.1152	0.1166	0.1272	0.1482	0.1190	0.1290	0.1687	0.1480	*0.1063*	0.6634
THB	0.3800	0.3736	*0.3513*	0.3762	0.3692	0.3514	0.3933	0.3758	0.3653	0.7853
T0=trunc(T.5)*										
CNY	0.0675	0.0662	0.0664	0.0672	0.0661	*0.066*	0.0683	0.0672	0.0986	0.4556
IDR	0.3752	0.3568	*0.3393*	0.3753	0.3500	0.3463	0.3719	0.3741	0.4040	2.7706
JPY	0.2297	0.2188	0.2217	0.2462	0.2167	0.2232	0.2463	0.2462	*0.2131*	0.6267
KRW	0.8759	0.8492	0.9374	0.8411	0.8468	0.8765	0.8454	0.8400	*0.6817*	1.2007
MYR	0.9333	0.8652	0.8678	0.8603	0.8645	0.8643	0.8817	0.8594	*0.7046*	1.5026
PHP	0.2837	0.3005	0.2923	0.2845	0.2967	0.2908	0.3035	*0.2834*	0.3136	0.6607
SGD	*0.1155*	0.1186	0.1300	0.1487	0.1224	0.1313	0.1661	0.1485	0.1173	0.5934
THB	0.4096	0.4118	*0.4053*	0.4342	0.4088	0.4081	0.4797	0.4337	0.4245	0.7189
T0=trunc(T.6)*										
CNY	0.0625	0.0616	0.0606	0.0658	0.0619	*0.0600*	0.0764	0.0657	0.0906	0.1065
IDR	0.3656	0.3422	0.3362	0.3664	0.3372	*0.3334*	0.3630	0.3652	0.3867	0.3816
JPY	0.3366	0.3302	0.3315	0.3547	0.3221	0.3329	0.3634	0.3541	*0.3125*	0.4091
KRW	0.9610	0.9187	0.9458	0.9079	0.9132	0.8965	0.8989	0.9072	*0.7386*	1.1474
MYR	0.9327	0.8657	0.8682	0.8609	0.8623	0.8607	0.8825	0.8600	*0.7099*	1.4382
PHP	0.2948	0.3029	0.2965	0.2968	0.2967	*0.2948*	0.3144	0.2961	0.3207	0.3496
SGD	*0.1192*	0.1207	0.1287	0.1425	0.1227	0.1298	0.1563	0.1421	0.1257	0.1898
THB	0.4205	0.4157	0.4190	0.4568	*0.4091*	0.4210	0.4929	0.4554	0.4273	0.5127
T0=trunc(T.7)*										
CNY	0.0639	0.0616	*0.0600*	0.0730	0.0623	0.0603	0.0944	0.0728	0.0997	0.1513
IDR	0.3626	0.3416	*0.3059*	0.3469	0.3284	0.3080	0.3548	0.3460	0.3802	0.3860
JPY	0.3504	0.3404	0.3495	0.3645	0.3326	0.3476	0.3832	0.3631	*0.3295*	0.3716
KRW	0.9102	0.8859	0.9032	0.8691	0.8783	0.8453	0.8638	0.8655	*0.6991*	0.8793
MYR	0.9862	0.9032	0.9045	0.8919	0.9003	0.8976	0.8947	0.8891	*0.7250*	1.5993
PHP	0.3009	0.3062	*0.2988*	0.3083	0.2992	0.3016	0.3353	0.3071	0.3154	0.3888
SGD	0.1204	*0.1200*	0.1281	0.1353	0.1236	0.1278	0.1539	0.1347	0.1254	0.2005
THB	0.4892	0.4660	0.4598	0.4892	0.4555	*0.4495*	0.5364	0.4882	0.4612	0.5099

The rolling mean absolute prediction error of daily returns of Thailand Baht is minimum when forecast with SUR. And almost countries can define the best model that can outperform in forecasting their daily returns.

2. Weekly Returns

There are four cases for different sizes of initial observations to measure forecasting performance as daily returns forecasting. The independence among countries increases for weekly period, there are more correlations among the weekly returns and the disturbances obtained from individual AR(1) than daily period considered earlier. And, also, the correlation matrices of weekly returns and disturbances obtained by individual AR(1) estimation are similar in their structure.

Table 12. Correlation Matrix of Weekly Returns

	CNY	IDR	JPY	KRW	MYR	PHP	SGD	THB
CNY	1.0000	0.0423	0.0782	0.2709	0.2292	0.0844	0.2735	0.0834
IDR	0.0423	1.0000	0.0207	0.3470	0.3804	0.4400	0.4586	0.1016
JPY	0.0782	0.0207	1.0000	0.3310	0.1866	0.0116	0.5848	0.3303
KRW	0.2709	0.3470	0.3310	1.0000	0.4832	0.2763	0.5952	0.3074
MYR	0.2292	0.3804	0.1866	0.4832	1.0000	0.4156	0.4717	0.2487
PHP	0.0844	0.4400	0.0116	0.2763	0.4156	1.0000	0.2798	0.1547
SGD	0.2735	0.4586	0.5848	0.5952	0.4717	0.2798	1.0000	0.3861
THB	0.0834	0.1016	0.3303	0.3074	0.2487	0.1547	0.3861	1.0000

Table 13. Correlation Matrix of Disturbances from Individual AR(1)

	CNY	IDR	JPY	KRW	MYR	PHP	SGD	THB
CNY	1.0000	0.0374	0.0843	0.2682	0.2147	0.0855	0.2841	0.0673
IDR	0.0374	1.0000	0.0278	0.3552	0.3894	0.4436	0.4381	0.0828
JPY	0.0843	0.0278	1.0000	0.3574	0.2433	0.0403	0.5756	0.3344
KRW	0.2682	0.3552	0.3574	1.0000	0.4803	0.2835	0.6064	0.3098
MYR	0.2147	0.3894	0.2433	0.4803	1.0000	0.3865	0.4891	0.2254
PHP	0.0855	0.4436	0.0403	0.2835	0.3865	1.0000	0.3161	0.1478
SGD	0.2841	0.4381	0.5756	0.6064	0.4891	0.3161	1.0000	0.3513
THB	0.0673	0.0828	0.3344	0.3098	0.2254	0.1478	0.3513	1.0000

The results on comparative forecasting models for weekly returns of 8 Asian countries show that there is no conclusive evidence to justify which model is the best among all of the competitive models. However, the SUR models could roughly yield less rolling mean absolute prediction error than the other models. This is according to the higher correlations among the disturbances from their individual AR(1) estimation.

One interesting point is that SUR is the best model to forecast Thailand Baht returns both daily and weekly period. And the minimum rolling mean absolute prediction error of Thailand Baht is small compare to rolling mean absolute prediction error of the other models.

Table 14. Rolling Mean Absolute Prediction Error of Weekly Returns

Initial T	Individual			Pool			Panel Model		Nonparametric Model	
Sample	OLS	SUR1	SUR2	Pool OLS	SUR1	SUR2	FE	RE	LPLS	LPWLS
T0=trunc(T.4)*										
CNY	0.0934	0.1009	0.0935	0.0993	0.1005	*0.0924*	0.1145	0.0994	0.0982	0.1130
IDR	0.5097	0.4936	0.4989	*0.4895*	0.4897	0.4939	0.4962	0.4896	0.5337	1.7330
JPY	0.6850	0.6865	*0.6519*	0.6735	0.6839	0.6524	0.7137	0.6762	0.6914	0.7115
KRW	0.5831	*0.5717*	0.6128	0.5918	0.5723	0.6121	0.5950	0.5947	0.5899	0.7309
MYR	0.5592	0.5594	0.5562	0.5767	0.5592	*0.5559*	0.5732	0.5778	0.5733	2.2500
PHP	0.5046	0.5602	0.5340	0.5041	0.5592	0.5284	0.5185	*0.5023*	0.5040	0.5368
SGD	0.3128	0.3172	0.3103	*0.3075*	0.3169	0.3095	0.3088	0.3082	0.3098	0.3117
THB	*0.7829*	0.8167	0.7879	0.7908	0.8192	0.7894	0.8436	0.7956	0.8047	0.8825
T0=trunc(T.5)*										
CNY	0.0930	0.1006	0.0916	0.0987	0.1010	*0.0909*	0.1152	0.0987	0.0994	0.1694
IDR	0.5887	0.5589	0.5616	0.5606	*0.5553*	0.5622	0.5666	0.5623	0.6865	1.4224
JPY	*0.6939*	0.7008	0.6981	0.7040	0.6981	0.7003	0.7616	0.7055	0.7101	0.8269
KRW	0.6099	*0.5841*	0.6367	0.6099	0.5849	0.6339	0.6087	0.6132	0.6117	0.7918
MYR	0.6062	*0.5965*	0.6011	0.6323	0.5970	0.6023	0.6327	0.6327	0.6354	0.8154
PHP	*0.4758*	0.5416	0.5397	0.5002	0.5409	0.5337	0.5232	0.4978	0.4894	0.5991
SGD	0.3288	0.3246	0.3301	0.3241	*0.3240*	0.3287	0.3278	0.3249	0.3264	0.3674
THB	0.7370	0.7630	*0.7298*	0.7341	0.7649	0.7330	0.7832	0.7373	0.8064	1.0048
T0=trunc(T.6)*										
CNY	0.0927	0.0960	0.0927	0.0981	0.0950	*0.0914*	0.1229	0.0980	0.0966	0.1017
IDR	0.6134	0.6013	0.5986	0.5952	0.5973	0.5952	0.6073	0.5954	*0.5892*	1.1322
JPY	0.7395	0.7347	0.7359	0.7396	*0.7305*	0.7402	0.7878	0.7392	0.7647	0.8913
KRW	0.5985	*0.5893*	0.6233	0.5991	0.5895	0.6202	0.6024	0.6028	0.6036	0.6639
MYR	0.6241	*0.6122*	0.6198	0.6488	0.6125	0.6209	0.6479	0.6494	0.6586	0.7193
PHP	*0.4906*	0.5477	0.5372	0.5071	0.5460	0.5316	0.5308	0.5047	0.5036	0.5384
SGD	0.3418	0.3442	0.3398	0.3417	0.3448	*0.3396*	0.3460	0.3419	0.3426	0.3506
THB	0.7344	0.7393	*0.7081*	0.7157	0.7450	0.7113	0.7628	0.7182	0.7659	0.8420
T0=trunc(T.7)*										
CNY	0.0901	0.0938	0.0901	0.0984	0.0924	*0.0896*	0.1317	0.0985	0.0999	0.0928
IDR	0.6001	0.5946	0.6070	0.5760	0.5951	0.6011	0.5924	0.5771	*0.5610*	1.4581
JPY	0.7378	0.7372	0.7302	0.7449	*0.7290*	0.7334	0.7937	0.7457	0.7749	2.0899
KRW	0.5918	0.5892	0.6249	0.5992	*0.5890*	0.6198	0.5986	0.6046	0.5946	0.6540
MYR	0.6062	0.5993	*0.5953*	0.6181	0.5996	0.5962	0.6158	0.6198	0.6213	2.2040
PHP	0.4931	0.5408	0.5208	0.4925	0.5398	0.5165	0.5028	0.4904	*0.4864*	0.4949
SGD	0.3408	0.3477	0.3435	*0.3346*	0.3466	0.3422	0.3386	0.3351	0.3378	0.3537
THB	0.7334	0.7326	*0.7021*	0.7110	0.7336	0.7035	0.7569	0.7120	0.7795	1.9328

5. Conclusion

This paper explores the effects of using the cross-section dependence information to evaluate the forecasting performance of the dynamic panel regression for Asia currencies on both daily and weekly returns. Additional forecasting for different simulated data generating processes is discussed.

The results of forecasting performance comparison show that:

1. Dynamic Panel Regression of Simulation Results

The study of six data generating processes, where each process has several combinations of N and T, are simulated to analyze the accuracy of forecasting performance on different incidental linear trends. The results show that the most simple homogeneous linear time trend with small variant normal disturbances should use pool OLS estimation to gain the forecasting performance. However, the similar smoothed structure of processes with heteroskedastic disturbances should be forecasted with the traditional Random Effects model. But the high volatile and idiosyncratic panel data should be forecasted by the nonparametric Local Polynomial Least Squares estimators.

2. Dynamic Panel Regression of Empirical Results

2.1) Daily Returns: The nonparametric local polynomial least squares (LPLS) could outperform the other models to forecast the daily returns as be measured by minimum rolling mean absolute prediction error. And if which country does not have LPLS as the best model, then the rolling mean absolute prediction error of that best model does not much different from the rolling mean absolute prediction error of the other models for that country.

2.2) Weekly Returns: There is no conclusive evidence to justify which model is the best among all of the competitive models. But, in general, the SUR models could yield minimum rolling mean absolute prediction error compared with the other models. This is according to the higher correlations among the disturbances, estimated from their individual AR(1) estimation, than the shorter period on daily returns.

In conclusion, the proposed nonparametric estimators could yield the improving performance on forecasting both in simulation and empirical applications. For simulation results, the nonparametric approach is effective when the simulated processes are idiosyncratic or highly volatile. For application results, we can see the similar outcome from the daily returns forecasting.

Furthermore, the study on the heterogeneous deterministic time trends with cross-section dependence could gain more understanding on cross-section dependent Asia currencies. Another previously cited bias-reduction or cross-section removing estimators are the prospective empirical research issues in the future.

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