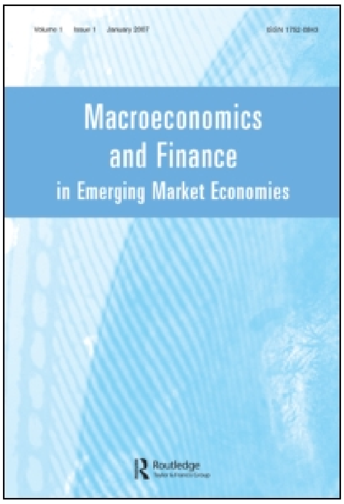

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Risk-based portfolio strategy in emerging stock markets: economic significance from Brazil, Russia, India and China

Aman Ullah [a]; Xiangdong Long [b]
[a] Department of Economics, University of California at Riverside, Riverside, CA, USA [b] Centre for Financial Analysis and Policy, University of Cambridge, Cambridge, UK

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RESEARCH ARTICLE

Risk-based portfolio strategy in emerging stock markets: economic significance from Brazil, Russia, India and China

Aman Ullah[a]* and Xiangdong Long[b]

[a]*Department of Economics, University of California at Riverside, Riverside, CA, USA;* [b]*Centre for Financial Analysis and Policy, University of Cambridge, Cambridge, UK*

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The purpose of this paper is to examine the conditional volatility and correlation predictability of four emerging stock markets, and address the issue whether investors could exploit this predictability to earn excess returns from the minimum variance portfolio of index component stocks. Inevitably, transaction cost affects the conclusive results. Nevertheless, economic gain exceeding a conservatively high transaction cost could be derived from a number of conditional volatility and correlation models. One dominant model, the shrinkage model, outperforms the market across the countries, cost structures and performance measures. We also document the superiority of averaging methodologies. However, semiparametric modelling falls in a grey area of profitability – sometimes attractive whilst sometimes not attractive.

Keywords: correlation; emerging stock market; performance measure; portfolio; volatility

1. Introduction

Emerging markets with distinguishing features of impressive returns and high volatility have challenged the research in finance for a long time. Harvey (1995) finds adding emerging market assets significantly enhances portfolio opportunities. Recently, some emerging equity markets, such as Brazil, Russia, India and China (in short, BRIC), have attracted lots of attention from investors. The well-documented success of quantitative strategies across developed markets, see Capaul, Rowley and Sharpe (1993), Fama and French (1998) and Rouwenhorst (1998), naturally motivates their applications on these emerging markets. Although stock selection is found to be as important as country selection by van der Hart, Slagter and van Dijk (2003) and is more attractive to investors, most of the research on portfolio strategies in emerging markets is at country level. Some exceptions investigating investment strategies of individual stock selection based on firm characteristics have rendered conflicting results: while Claessens, Dasgupta and Glen (1998) report a premium for large firms and growth stocks, Fama and French (1998) document a premium for small firms and value stocks. Deviating from the existing literature on predicting return through some firm-level accounting characteristics, our stock selection within one country tries to understand risk in emerging equity markets through exploring time series price data, which is publicly available. By modelling conditional volatility and correlation, adding value to investors in the form of significant excess return relative to the benchmark is the main purpose of this paper.

*Corresponding author. Email: aman.ullah@ucr.edu

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Since the seminal paper of Engle (1982) and its followed plethora of extending the autoregressive conditional heteroscedasticity (ARCH) model, describing and forecasting changes in the volatility of financial time series become a prosperous subfield in empirical finance. For a survey of ARCH-type models, see Bollerslev, Engle and Nelson (1994). A range of multivariate models have been developed to address some questions related to asset allocation, portfolio risk evaluation and dynamic portfolio analysis, which are of interest to both academia and financial practitioners. For the recent survey of multivariate models, see Bauwens, Laurent and Rombouts (2006). The following problems are the frequently asked questions (FAQs) posted to financial econometricians: Will the shock to one stock transmit to other stocks? How will this affect investors' portfolio choices? Is it possible to determine an optimal model across different financial situations? Are the findings in emerging markets consistent with those in developed countries? And, in the present state of the art, could investors earn excess returns through these models?

Besides Monte Carlo tests, Bauwens, Laurent and Rombouts (2006) review three types of diagnostics for multivariate conditional heteroscedasticity models in the literature: the portmanteau tests of the Box–Pierce–Ljung type, the residual-based diagnostics and the Lagrange multiplier tests. To overcome the unobservable of the volatility in the standard forecasting evaluation technique, like root mean square forecast errors, Pesaran and Zaffaroni (2006) propose a Value-at-Risk diagnostic test to evaluate the multi-asset volatility models including averaging models. McAleer (2005) emphasizes that the purpose of developing econometric modelling is for usage in practice. Regardless of theoretical significance, indeed there is little value for those techniques never being used in real-life practice. A natural complement to statistical tests for model evaluation is to compare different models' economic gain. The major objective of this paper is to answer the above FAQs via assessing the economic gain of the existing econometric methodologies.

The literature on portfolio performance measurement goes back to the early work of Jensen (1968), Sharpe (1966) and Treynor (1965). Most empirical analyses use the equilibrium-based asset-pricing models, like the CAPM and the APT, to evaluate portfolio performance by estimating the risk-adjusted performance. By imposing the law of one price, Chen and Knez (1996) demonstrate that the Jensen measure, the APT-based measures and the measures in Glosten and Jagannathan (1994) are all representable in their general form of admissible performance measures. In addition to the averaged value of portfolio return over the investment period, we measure portfolio performance through the methodologies in Sharpe (1966), Jensen (1968), Fama and French (1993), and Carhart (1997): the first one is the Sharpe ratio, which is the portfolio's return earned per unit of total risk and is positively correlated with the portfolio performance; the last three measures are of the same type and they are the intercepts of the single or multiple factor performance regressions. Note that a significantly positive (negative) intercept called alpha in finance terminology, indicates superior (inferior) portfolio performance.

We employ most of the conditional volatility and correlation models in both the academic literature and ad hoc practitioner manuals to construct the minimum variance portfolio of index component stocks in these four emerging stock markets. Our results are striking in the form of the portfolio performance measures mentioned above. The margin is large enough to absorb the transaction costs in these markets. The extra return from the shrinkage model is robust to cost scenarios and invested countries regardless of performance measures. The wavering performance of semiparametric skills leads one to conclude more effort should be spent on optimal bandwidth searching. After evaluating their real-time track record, the averaging methodologies, especially 'thick', convince us of their ability to systematically generate excess returns in these emerging stock markets.

The plan of the paper is as follows: Section 2 discusses different types of multivariate conditional volatility and correlation models, shows averaging methodologies, describes the investment process, introduces the minimum variance portfolio, and presents the portfolio performance evaluation methods. Section 3 is the playing fields of applying all these models on the four emerging stock markets that we are interested in. Finally, Section 4 summarizes our main findings.

2. Methodology

We are interested in modelling the $k \times k$ conditional covariance matrix H_t of the $k \times 1$ asset return vector $\mathbf{r}_t$ with the $k \times 1$ conditional mean $\boldsymbol{\mu}_t$

$$\mathbf{r}_t = \boldsymbol{\mu}_t + \mathbf{H}_t^{1/2}\boldsymbol{\xi}_t$$
$$\boldsymbol{\xi}_t|\Phi_{t-1} \sim F(\mathbf{0}, \mathbf{I}_k)$$

where Φ_{t-1} is the information set (σ-field) at time $t-1$ and F is the conditional joint distribution of the $k \times 1$ error vector $\boldsymbol{\xi}_t$, which has zero mean and identity covariance matrix. In real time, the challenge of making excess returns facing investors with quantitative modelling skills starts from specifying the conditional joint distribution function, conditional mean and conditional covariance matrix. Modelling $\boldsymbol{\mu}_t$ is beyond the scope of this paper and we simply assume $\boldsymbol{\mu}_t$ being zero; for $\mathbf{H}_t$, many specifications are discussed below; and because of the robustness in a large sample, F is assumed to be multivariate normal.

2.1. *Volatility and correlation modelling*

Considerable literature has accumulated over the years regarding conditional volatility and correlation modelling. Pesaran and Zaffaroni (2006) interpret much of these models within the framework of Bollerslev's decomposing $\mathbf{H}_t$ as $\mathbf{D}_t\mathbf{R}_t\mathbf{D}_t$ (1990), where $\mathbf{D}_t$ is a $k \times k$ diagonal matrix with diagonal element $\sqrt{h_{ii,t}}$ and $\mathbf{R}_t$ is a conditional correlation matrix with unit diagonal elements and off-diagonal elements $\rho_{ij,t}$, $i \neq j$, $i,j = 1, \ldots, k$. In both fields of ad hoc practitioner manuals and academic literature most of the conditional volatility and correlation models could be classified by characteristics of $\mathbf{D}_t$ and $\mathbf{R}_t$. The long list includes, for example, the equal-weighted moving average (EQMA) model, the exponential-weighted moving average (EWMA) model, the mixed moving average (MMA) model, the generalized exponential-weighted moving average (GEWMA) model, the constant conditional correlation (CCC) model by Bollerslev (1990), and the dynamic conditional correlation (DCC) model by Engle (2002). An excellent summary for these models can be found in the 'Supplement' for Pesaran and Zaffaroni (2006).

A necessary condition for the positive definite of $\mathbf{H}_t^{\text{EQMA}} = (1/N)\sum_{i=1}^{N}\mathbf{r}_{t-i}\mathbf{r}'_{t-i}$ in the EQMA model is the window length N should be bigger than the asset dimension k : we try 100 and 150 for N in our empirical analysis. The exponential weight in the EWMA model implicitly assumes the shock's effect vanishing at an exponential speed. The non-singularity of the conditional covariance matrix implies one necessary condition in the EWMA model: the smoothing weight λ^{i-1} should not converge to zero too fast. Note this sharply narrows the range of λ and drives it around the optimal value of 0.94 set by J.P. Morgan (1996), especially when K is very large in real practice: we try 0.90, 0.92, 0.94 and 0.96 for λ. One implied assumption in the EWMA model is that both conditional variance and conditional correlation respond at exactly the same pace to shocks because λ smoothes both diagonal and off-diagonal elements in

$\mathbf{H}_t^{\text{EWMA}} = [(1-\lambda)/(1-\lambda^N)]\sum_{i=1}^{N}\lambda^{i-1}\mathbf{r}_{t-i}\mathbf{r}'_{t-i}$. De Santis et al. (2003) modify the EWMA model to incorporate different response speeds by splitting λ into λ_1 and λ_2 where $\lambda_1(\lambda_2)$ controls weights for $\mathbf{D}_t^{\text{EWMA}}$ ($\mathbf{R}_t^{\text{EWMA}}$) as

$$(\mathbf{D}_t^{\text{EWMA}})^2 = \frac{1-\lambda_1}{1-\lambda_1^N}\sum_{i=1}^{N}\lambda_1^{i-1}[\text{diag}(\mathbf{r}_{t-i})]^2$$
$$\mathbf{Q}_t^{\text{EWMA}} = \frac{1-\lambda_2}{1-\lambda_2^N}\sum_{i=1}^{N}\lambda_2^{i-1}\mathbf{r}_{t-i}\mathbf{r}'_{t-i}$$

where $\mathbf{Q}_t^{\text{EWMA}}$ is the matrix of weighted variances and covariances such that

$$\mathbf{R}_t^{\text{EWMA}} \equiv [\text{diag}(\mathbf{Q}_t^{\text{EWMA}})]^{-1/2}\mathbf{Q}_t^{\text{EWMA}}[\text{diag}(\mathbf{Q}_t^{\text{EWMA}})]^{-1/2}.$$

Both λ_1 and λ_2 are calibrated a priori, and $\lambda_1 \geq \lambda_2$ reflects the fact that volatility responds faster than correlation to shocks. The value of λ_2 is determined by the intersection of the set {0.90, 0.92, 0.94, 0.96} and its upper bound λ_1. Another modification direction is the MMA model, which combines the EQMA model for $(\mathbf{D}_t^{\text{MMA}})^2 = (1/N)\sum_{i=1}^{N}[\text{diag}(\mathbf{r}_{t-i})]^2$ and the EWMA model for $\mathbf{Q}_t^{\text{MMA}} = [(1-\lambda_2)/(1-\lambda_2^N)]\sum_{i=1}^{N}\lambda_2^{i-1}\mathbf{r}_{t-i}\mathbf{r}'_{t-i}$ together. The success of the generalized autoregressive conditional heteroscedasticity (GARCH) model by Bollerslev (1986) motivates the substitution of $\mathbf{D}_t^{\text{EWMA}}$ by $\mathbf{D}_t^{\text{GEWMA}}$:

$$(\mathbf{D}_t^{\text{GEWMA}})^2 = \text{diag}(\omega) + \sum_{i=1}^{p}\text{diag}(\alpha_i)\circ\mathbf{r}_{t-i}\mathbf{r}'_{t-i} + \sum_{j=1}^{q}\text{diag}(\beta_j)\circ(\mathbf{D}_{t-j}^{\text{GEWMA}})^2$$

where α_i represents the ARCH effects (or the shock's short-run effect), β_j represents the GARCH effects (or the shock's long-run effect), $\sum_{i=1}^{p}\alpha_i + \sum_{j=1}^{q}\beta_j$ represents the long-run persistence, and $\circ$ is the Hadamard product (or element-by-element multiplication) of two identically sized matrices. The structure of $\mathbf{Q}_t$ in the GEWMA model is the same as that in the MMA model. In the EWMA, MMA and GEWMA models, $\mathbf{R}_t = [\text{diag}(\mathbf{Q}_t)]^{-1/2}\mathbf{Q}_t[\text{diag}(\mathbf{Q}_t)]^{-1/2}$ is used to calculate $\mathbf{H}_t$ with $\mathbf{D}_t^{\text{EWMA}}$, $\mathbf{D}_t^{\text{MMA}}$ and $\mathbf{D}_t^{\text{GEWMA}}$ by $\text{H}_t = \mathbf{D}_t\mathbf{R}_t\mathbf{D}_t$.

Bollerslev (1990) uses $\mathbf{D}_t\mathbf{R}_t\mathbf{D}_t$ to decompose $\mathbf{H}_t$ in the likelihood function

$$L = -\frac{Tk}{2}\log 2\pi - \frac{1}{2}\sum_{t=1}^{T}\log|\mathbf{D}_t^{\text{CCC}}\mathbf{R}_t^{\text{CCC}}\mathbf{D}_t^{\text{CCC}}| - \frac{1}{2}\sum_{t=1}^{T}\boldsymbol{\xi}'_t(\mathbf{D}_t^{\text{CCC}}\mathbf{R}_t^{\text{CCC}}\mathbf{D}_t^{\text{CCC}})^{-1}\boldsymbol{\xi}_t$$

where $\mathbf{D}_t^{\text{CCC}}$ is modelled through a GARCH model as $\mathbf{D}_t^{\text{GEWMA}}$, and further simplifies the computation by assuming $\mathbf{R}_t^{\text{CCC}} = \text{R}$, whose maximum likelihood estimate is given by the sample analogue following the seemingly unrelated regressions (SUR) analogue. As such, there is no curse-of-dimension during parameter estimation even for a high-dimensional multivariate model. This constant assumption is modified to be time-varying through a GARCH-type process in the DCC model by Engle (2002):

$$\mathbf{Q}_t^{\text{DCC}} = (1-a-b)\overline{\mathbf{Q}} + a(\varepsilon_{t-1}\varepsilon'_{t-1}) + b\mathbf{Q}_{t-1}^{\text{DCC}}$$

where $\varepsilon_t \equiv (\mathbf{D}_t^{\text{DCC}})^{-1}\mathbf{r}_t$ and $\mathbf{D}_t^{\text{DCC}} = \mathbf{D}_t^{\text{CCC}}$, $\overline{\mathbf{Q}}$ is the sample covariance matrix of ε_t, and the appropriate standardization

$$\mathbf{R}_t^{\text{DCC}} = [\text{diag}(\mathbf{Q}_t^{\text{DCC}})]^{-1/2}\mathbf{Q}_t^{\text{DCC}}[\text{diag}(\mathbf{Q}_t^{\text{DCC}})]^{-1/2}$$

keeps $\mathbf{R}_t^{\mathrm{DCC}}$ both positive definite and unit diagonal elements. Variance targeting, the simple useful trick introduced by Engle and Mezrich (1996), could reduce the dimensions of the unknown parameters. The two-stage estimation makes the DCC model attractive for its fast iteration convergence speed although the two-stage estimation would be less efficient than the one-stage estimation.

Of course, not every conditional volatility and correlation model follows this modelling path. The widely used scalar BEKK model by Engle and Kroner (1995) directly models $\mathbf{H}_t$ as a multivariate extension of the univariate GARCH model:

$$\mathbf{H}_t^{\mathrm{BEKK}} = \left(1 - \sum_{i=1}^{p} a_i - \sum_{j=1}^{q} b_j\right)\overline{\mathbf{H}} + \sum_{i=1}^{p} a_i(\mathbf{r}_{t-i}\mathbf{r}_{t-i}') + \sum_{j=1}^{q} b_j\mathbf{H}_{t-j}^{\mathrm{BEKK}}$$

where $\overline{\mathbf{H}}$ is the sample covariance matrix of $\mathbf{r}_t$. This variance-targeting skill assumes the convergence of the sample moment to population moment when $\mathrm{T} \to \infty$.

Another major trend of modelling high-dimensional assets is extracting common factors. This could be tracked back to Sharpe's single-index model (1963). In addition to an overall market factor, Fama and French (1993) consider two observable factors related to firms' size and book-to-market equity. Another refinement to the single-index model is to study firms' industry property: Fama and French (1997) assign each company into one of 48 industries. Some companies, like BARRA, also use proprietary methods to construct non-industry-based factors. Except for the first factor being treated as the market index, the factors derived from principal component analysis have little economic interpretation. Harvey, Ruiz and Sentana (1992) apply the Kalman filter to extract the information about the unobservable factor and estimate the unknown parameters via quasi-maximum likelihood estimation. The factor GARCH (F-GARCH) model by Diebold and Pesaran (1999) uses averaged asset return to consistently estimate the factor $\hat{f}_t = (1/k)\sum_{j=1}^{k} r_{jt}$ and regresses the return vector $\mathbf{r}_t$ on this constructed factor, $\mathbf{r}_t = \mathbf{b}_0\hat{f}_t + \mathbf{e}_t$. The joint conditional distribution of $\hat{f}_t$ and $\mathbf{e}_t$ are assumed to be multivariate normal with zero mean and diagonal conditional covariance matrix $\mathrm{diag}(\phi_t,\Pi_t)$, where scalar ϕ_t and diagonal matrix Π_t are modelled as

$$\phi_t = c + \sum_{i=1}^{p} a_i\hat{f}_{t-i}^2 + \sum_{j=1}^{q} b_j\phi_{t-j}$$

$$\Pi_t = \mathrm{diag}(\omega) + \mathrm{diag}(\alpha) \circ \hat{\mathbf{e}}_{t-1}\hat{\mathbf{e}}'_{t-1} + \mathrm{diag}(\beta) \circ \Pi_{t-1}.$$

The orthogonal GARCH (O-GARCH) model by Alexander (2001) first models the diagonal conditional covariance matrix Ψ_t of $\mathbf{s}_t = \mathrm{W}(k)\mathbf{r}_t$ as

$$\Psi_t = \mathrm{diag}(\omega) + \sum_{i=1}^{p} \mathrm{diag}(\alpha_i) \circ \mathbf{s}_{t-i}\mathbf{s}_{t-i}' + \sum_{j=1}^{q} \mathrm{diag}(\beta_j) \circ \Psi_{t-j}$$

where $\mathbf{W}(k) = (\mathbf{w}_1, \ldots, \mathbf{w}_k)$ are k eigenvectors of $\tilde{\mathbf{S}}_T = (\sum_{t=1}^{T} \tilde{\mathbf{r}}_t\tilde{\mathbf{r}}_t')/T$ and each element $\tilde{r}_{jt}$ of $\tilde{\mathbf{r}}_t$ is normalized by its sample mean $\bar{r}_j$ and sample standard deviation, $\bar{s}_j$; then derives $\mathbf{H}_t$ as

$$\mathbf{H}_t = \mathbf{VW}(k)\Psi_t\mathbf{W}(k)'\mathbf{V}$$

where $\mathbf{V} = \mathrm{diag}(\bar{s}_1, \ldots, \bar{s}_k)$.

Pesaran and Zaffaroni (2006) use and average these models to estimate and forecast the conditional covariance matrix among 22 main industry indices of the Standard & Poor's

500. Given the associated computational complexities, we do not consider the model of Harvey, Ruiz and Sentana (1992); instead, the shrinkage model by Ledoit and Wolf (2003) and the semiparametric multivariate GARCH (SMGARCH) model by Long, Su and Ullah (2007) are added to the toolbox. The shrinkage model is a weighted average of the single-index covariance matrix estimator like Sharpe (1963) and the sample covariance matrix. The essence is to estimate optimal weight through minimizing the Frobenius norm of the difference between the shrinkage estimator and the true covariance matrix. The SMGARCH model uses a kernelled non-parametric estimator, $\mathbf{H}_t^{np} = \sum_{s=1}^{T} \xi_s \xi_s' K_h(\boldsymbol{x}_s - \boldsymbol{x}_t) / \sum_{s=1}^{T} K_h(\boldsymbol{x}_s - \boldsymbol{x}_t)$, for the conditional covariance matrix of $\xi_t = (\mathbf{H}_t^p)^{-1/2}\mathbf{r}_t$ to get a sandwich-form combined estimator $\mathbf{H}_t^{sp} = (\mathbf{H}_t^p)^{1/2}\mathbf{H}_t^{np}(\mathbf{H}_t^p)^{1/2}$, where $\mathbf{H}_t^p$ is the parametric estimator of the conditional covariance matrix for $\mathbf{r}_t$, $\boldsymbol{x}_t$ is a $d \times 1$ vector of state variables (in this paper, we use one-period lagged return of the stock index for Brazil, Russia and India, and that of simple average of existing component stock prices because China's stock index is valid only for a short period), and $k_h(.)$ is the kernel function with bandwidth $h = (h_1, \ldots, h_d)$. In the case that the parametric model is correctly specified, $\mathbf{H}_t^{np}$ collapses to the identity matrix and there is no difference between semiparametric and parametric models. A well-known fact in non-parametric econometrics is that model performance is more sensitive to bandwidth choice than kernel function choice. Because of this, we consider three variants of h_j as grid searching, using $c = 0.5$, 1 and 2 in $h_j = c\bar{s}_j T^{-1/6}$, $j = 1, \ldots, d$, while the multivariate Gaussian density function with identity correlation matrix is applied for the kernel function. Both the Akaike information criterion (AIC) and Schwarz Bayesian information criterion (SIC) are applied to choose c_{optimal} for each semiparametric model at each period and they actually lead to the same results.

2.2. *Average models*

Assume the universal model set is $\mathrm{M} = \cup_{j=1}^{m} \{M_j\}$ where m is the total number of models under consideration. We study 41 'underlying' models (including 2 EQMA models, 7 EWMA models, 6 MMA models, 8 GEWMA models, 4 CCC models, 4 BEKK models, 4 DCC models, 1 OGARCH model, 1 shrinkage model and 4 FDP models) and 18 semiparametric models (including 4 SCCC models, 4 SBEKK models, 4 SDCC models, 1 SOGARCH model, 1 SShrinkage model and 4 SFDP models). In SCCC, SBEKK, SDCC, SOGARCH, SShrinkage and SFDP, the first capital S indicates it is a semiparametric model. In total, $m = 59$. Each M_j specifies $\boldsymbol{\mu}_t$, $\mathbf{H}_t$ and F. In reality, current standard 'thin' modelling of selecting one best model based on the model selection criteria from many alternative specifications and then forecasting is not optimal because it does not utilize any information in the alternative models.

There are different mechanisms to set weights $\theta_{j,t-1}$ to model M_j at time $t-1$ for the purpose of averaging $\mathbf{H}_{j,t}$ across models:

$$\mathbf{H}_t = \sum_{j=1}^{m} \theta_{j,t-1} \mathbf{H}_{j,t}$$

where $\mathbf{H}_{j,t}$ is the conditional covariance matrix estimator/forecaster at time t from model j. The simple one is equal weight: $\theta_{j,t-1} = 1/m$. Combination forecasting, even a simple average with equal weight, will be better than forecasting from a single model. From a substantial body of literature on the combination of forecasts, Clemen (1989) summarizes two primary conclusions: (1) the combined forecasts can substantially reduce the errors of the component forecasts; and (2) the more sophisticated combinations do not perform better than the simple average one. Furthermore, he forecasts 'combining forecasts should become part of the mainstream of forecasting practice' (Clemen 1989, p. 559). Other than these, Granger (1989) illustrates some general points through a simple analysis: (1) aggregating forecasts is not equal to aggregating information sets; (2) weights are not necessarily non-negative; and (3) the more forecasts included for combination, the better. Actually, as Granger (1989) points out, in practice there is still space left by component forecasts for combined forecasts to improve although there is no reason to always credit combined forecasts as the best possible forecasts. Time-varying combined weights discussed by Engle, Granger and Kraft (1984) do not get recommendation from Granger (1989) because of its divergence from simplicity. Granger and Jeon (2004) recommend a pragmatic way of 'thick' modelling: discarding poor performance models based on AIC or SIC and equally weighting the surviving models, such as top 25% models. Achour et al. (1999) use attribute-based stock selection methodology to study stock selection in emerging markets. Their method of sorting firms by some factors into a predefined number of portfolios is analogous to equal-weighted averaging of models surviving from model selection criteria in Granger and Jeon (2004).

Another trend of averaging model is Bayesian model averaging (BMA) method, see Hoeting et al. (1999) for a detailed tutorial. Besides the computational issues, specifying model space, choosing the prior probability of model M_j and setting the prior probability of unknown parameters conditional on model M_j impede BMA from being widely applied, especially in our current context of high-dimensional models. The posterior probability of unknown parameters conditional on model M_j and that of model M_j are two other challenges facing practitioners. For the former problem, one could seek help from asymptotical normal theory; and for the latter, one can consider either AIC (see Burnham and Anderson 1998) or SIC following Draper (1995) to approximate the posterior probability of model M_j. The corresponding weight of model M_j at time $t-1$ is $\theta_{j,t-1} = \exp(\varphi_{j,t-1})/\Sigma_{j=1}^{m} exp(\varphi_{j,t-1})$ where $\varphi_{j,t-1}$ is either $\mathrm{AIC}_{j,t-1} - \max_j(\mathrm{AIC}_{j,t-1})$ or $\mathrm{SIC}_{j,t-1} - \max_j(\mathrm{SIC}_{j,t-1})$. Garratt et al. (2003) adopt this methodology for probability forecasting in the framework of a small long-run structural vector error-correcting autoregressive model of the UK economy; and Pesaran and Zaffaroni (2006) provide a pragmatic implementation of the BMA approach on volatility modelling of large-dimensional assets. All these five averaging methods (simple equal weighting, AIC-based 'thick', SIC-based 'thick', AIC-based BMA and SIC-based BMA) are tried in this paper.

2.3. *Portfolio and trading*

In our analysis, the investors recursively estimate and forecast the conditional covariance matrix of interested asset returns, and then employ the recursive forecasts in the portfolio investment strategy. In this subsection, we explain the risk-based portfolio strategy and the mock trading procedure in more details. For the concerns about the relative contribution of covariance matrix modelling to portfolio selection with respect to expected return modelling, Ledoit and Wolf (2003) argue that 'any reduction in risk translates into an increase in expected returns' and justify 'concentrate on the covariance matrix alone without worrying about expected returns' (p. 614). Following their logic, the challenge of modelling expected returns is left for another forum. Note that a recursive modelling approach is employed by Pesaran and Timmermann (1995) to predict the stock return.

Whilst the relatively passive buy-and-hold investment strategy is to some extent immune to trading costs, the profitability of our recursive predictions may be eroded by transaction costs. To compare portfolio performance, we should not ignore transaction costs associated with the frequent turnover (stamp duty, brokerage fees and bid–ask spreads for securities transactions): we can either use a fixed percentage of price as transaction cost or substitute it by half spread between the high and low prices. The volatile change and wide range of spreads, however, make us pick up the former one as the choice. To show the effect of transaction cost on portfolio performance, we make use of three fixed rates of transactions: (1) zero cost; (2) 50 basis points; and (3) 100 basis points.

For the purpose of testing whether recursive forecasts could generate extra return relative to the market under cost scenarios, we put to use our forecasts in one extensively hired investment strategy in our implementation: the minimum variance portfolio, which the risk-averse investors choose by minimizing portfolio variance $\boldsymbol{\omega}'_t\mathbf{H}_t\boldsymbol{\omega}_t$ under the subject of unit summed weights:

$$\boldsymbol{\omega}_t = \frac{\mathbf{H}_t^{-1}\boldsymbol{\iota}}{\boldsymbol{\iota}'\mathbf{H}_t^{-1}\boldsymbol{\iota}}$$

where $\boldsymbol{\iota}$ is a $k \times 1$ unit vector.

Investors start off with 1 billion units of local currency at the beginning of the investment period and reinvest the portfolio income every month. Also, to be like 'real-time' trading, there are some trading rules we should follow, for example, the trading volume should be an integer times the minimum trading volume, which is set at 100 shares in our study. We downloaded all data in April 2007 and this hides some survivorship-bias-type information investors could not observe at the time of making their decisions before 2007. However, considering all stocks we study are mainly blue-chip index component stocks, this survivorship bias should not change our conclusion because the default probabilities of index component stocks are extremely small if any. The component property of these stocks also alleviates our worries about the liquidity risk of this most liquid class of shares available to local investors.

2.4. *Performance measure*

For each portfolio, we estimate the risk-adjusted performance by employing the Sharpe ratio, the standard Jensen (1968, 1969) alpha, Fama and French's 3-factor model (1992a, 1993) and Carhart's 4-factor model (1997). Denote $R_{i,t}$ as the portfolio return using conditional volatility and correlation model i at period t, where $i = 1, \ldots ,68$. The Sharpe ratio is $S_i = \mu_{i,R}/\sigma_{i,R}$, where $\mu_{i,R}$ and $\sigma_{i,R}$ are the sample mean and sample standard deviation of $R_{i,t} - R_{f,t}$, and $R_{f,t}$ is the risk-free return at time t.

Jensen's alpha, a typical measure of superior/inferior performance relative to a market proxy, is the intercept of the following time series regression:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{1,i}(R_{m,t} - R_{f,t}) + \varsigma_{i,t}$$

where $R_{m,t}$ is the return of the benchmark portfolio, like market index, at time t; $R_{m,t} - R_{f,t}$ is understood as an overall market factor; the portfolio's systematic risk, $\beta_{1,i}$, indicates how sensible the portfolio is to the benchmark portfolio return; and $\varsigma_{i,t}$ is an error term. The sign of α_i demonstrates the risk-adjusted performance of the portfolio using conditional volatility and correlation model i relative to the benchmark portfolio: the significantly positive is the evidence in support of the superiority while the significantly negative verifies inferior performance. Extension to the two-index benchmark including both equity index and government bond index is motivated by the fact that US equity funds hold bonds in their portfolio, see Blake, Elton and Gruber (1993). In our study, however, selecting stocks only from index component stocks makes us free from the concern of the two-index benchmark.

Fama and French (1993, 1997) and Chan, Jegadeesh and Lakonishok (1996) challenge the explanation adequacy of this single-index model to portfolio behaviour. Being consistent with a market equilibrium model with three risk factors, Fama and French (1992a, 1993) attribute securities return in excess of the risk-free rate to three elementary factors:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{1,i}(R_{m,t} - R_{f,t}) + \beta_{2,i}\mathrm{SMB}_t + \beta_{3,i}\mathrm{HML}_t + \varsigma_{i,t}$$

where SMB_t is the return difference between a portfolio of small market capitalization stocks and a portfolio of large market capitalization stocks at time t, and HML_t is the return difference between a portfolio of high book-to-market stocks and a portfolio of low book-to-market stocks at time t. The coefficients and premia on the factor-mimicking portfolios, $\beta_{1,i}$, $\beta_{2,i}$ and $\beta_{3,i}$, indicate the sensibility of portfolio excess return with respect to these three factors. For simplicity, denote ME and BE as the firm's market value and book value, respectively.

In addition to three elementary strategies (high vs. low beta stocks, large vs. small market capitalization stocks, value vs. growth stocks) implied in Fama and French's 3-factor model, Carhart (1997) also adopts the strategy of buying winners and selling losers in Jegadeesh and Titman (1993) and adds an additional factor, Mom_t, to capture one-year momentum anomaly:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{1,i}(R_{m,t} - R_{f,t}) + \beta_{2,i}\mathrm{SMB}_t + \beta_{3,i}\mathrm{HML}_t + \beta_{4,i}\mathrm{Mom}_t + \varsigma_{i,t}$$

where Mom_t is the difference in return between a portfolio of the past 12 months' winners and a portfolio of the past 12 months' losers at time t. Recall that the significantly positive α_i indicates the superior performance of the portfolio using model i relative to the benchmark.

3. The playing fields

In the previous section, we detailed the methodological approaches we use to construct portfolios and assess portfolio performance. In this section we describe the data and the factors for performance evaluation, and present the common features of the results. The investors start off with 1 billion units of local currency, rebalance the portfolio based on one-step-ahead forecasts of conditional covariance matrix at the beginning of each month throughout the investment period. The investors invest all accumulated portfolio wealth while keeping the extra tiny part of wealth in the form of cash, which is left aside due to the trading rule's constraint. Compared to the high computation requirement of daily updating, this monthly rebalancing is more practical.

3.1. Data and recursive modelling approach

Different from the so-called top-down asset allocation, we do not explicitly consider country-level analysis, like analysing either domestic or external macroeconomic factors.

Instead, our study focuses on the risk-based stock selection decision within the country and treats country selection as a decision already made. Recently, investors have become interested in four emerging stock markets: Brazil, Russia, India and China. As a result, we apply the conditional volatility and correlation modelling skills on index component stocks in BRIC, construct minimum variance portfolio evaluate the track records of these portfolios, and especially test whether the generated excess returns relative to the benchmark are significant. The powerful information asymmetries between local investors and international traders, which is emphasized by Achour et al. (1999), and the foreign exchange risk enable us to mimic local investors' real-time decisions on the basis of the daily price denominated in local currency.

From Datastream, we download daily close price data of index component stocks in BRIC after adjusting for splits, dividends and rights offerings. Table 1 provides descriptive statistic information on the index's daily logarithm return, which is computed as 100 times the difference between logarithm prices of two consecutive trading days. The Datastream codes for four stock indices are Brboves for Bovespa Stock Index in Brazil, Rsrtsin for Russian Trading System (RTS) Index in Russia, Ibomsen for Bombay Stock Exchange (BSE) 30-share sensitive index in India, and Chsh50I for Shanghai Stock Exchange (SSE) 50 index in China. Our sample period is January 1999–December 2006 for Brazil, Russia and India, but January 1998–December 2005 for China. In 2006, the Chinese government started non-tradable share reform. This reform froze trading of most stocks involved for one to two months during the compensation negotiation process. Because of this reason, we shift sample period one year earlier for China. One feature of stock indexes in these emerging markets is the time-varying amount of component stocks included in these indexes: 5 new companies appear in Ibomsen while 29 new stocks show up in Chsh50I; for Brboves and Rsrtsin, the component stock number increases from 12 to 58, and from 27 to 49. The increasing rates of component stock amount in BRIC are 38.10, 81.48, 20.00 and 223.08% in that order.

The return and risk trade-off is clearly observed in these index data: Russia has both the highest sample mean of daily return (0.08%) and the highest sample standard deviation (1.00) and China has both the lowest averaged daily return (0.01%) and the lowest sample standard deviation (0.62). All kurtosis values are bigger than 3, and the high chances of extreme events implied show the significance and the necessity of modelling risk for investors in these emerging markets. The last column reports the Ljung–Box statistic of order 20 for autocorrelation testing. To avoid the effect of newly listed stocks, at each rebalancing time we only consider those stocks having been listed for at least two

Table 1. Summary statistics.

Country	Sample period	Number at start	Number at end	Mean	St. dev.	Skewness	Kurtosis	Ljung–Box (20)
Brazil	01/99–12/06	42	58	0.04	0.85	1.33	23.33	35.16
Russia	01/99–12/06	27	49	0.08	1.00	−0.15	4.06	48.52
India	01/99–12/06	25	30	0.03	0.67	−0.39	4.47	40.83
China	01/98–12/05	13	42	0.01	0.62	0.73	6.83	26.18

Note: Column 2 is the sample period; columns 3 and 4 are stock numbers at start date and at end date; and columns 5–9 report the sample mean, standard deviation, skewness, kurtosis and Ljung–Box statistic of order 20 for logarithm daily return of stock index. For China, this stock index is the simple average of the daily close price of the existing component stocks.

years for portfolio construction. Another automatic filter criterion is: we screen out all stocks with more than 10 consecutive zero daily returns within the rolling-window sample period.

For the purpose of out-of-sample forecasting, there are three schemes for in-sample estimation: (1) using the whole existing samples from the beginning $\{\mathbf{r}_t, \ldots ,\mathbf{r}_1\}$; (2) the rolling sample $\{\mathbf{r}_t, \ldots ,\mathbf{r}_{t-R+1}\}$ of size R; and (3) a fixed sample $\{\mathbf{r}_R, \ldots ,\mathbf{r}_1\}$ at the end of the in-sample. The first one could be treated as a special case of scheme two where the rolling window is expanding. The third scheme is applied when recursive estimations in schemes one and two are to a great extent time-consuming. At the beginning of each month from 2001 to 2006 for Brazil, Russia and India and from 2000 to 2005 for China, all models are re-estimated using data of the past two years. This two-year rolling window is chosen arbitrarily and has remained unchanged throughout the six-year investment period. Although this rolling-window method does not use information as much as possible as the expanding-window method, two reasons led us to it: (1) the longer sample period, the higher possibility for structure break, which is common in emerging market data; and (2) some stocks are not available for trading at the sample beginning. For example, there were only 13 stocks in Chsh50I in December 1998 satisfying our two data filter rules, while this number increased to 29 in November 2005.

3.2. Common variation in returns

Lehman and Modest (1987) document the effect of benchmark choice on the performance evaluation. Both value-weighted and equal-weighted returns of all stocks listed at the stock exchange are used in the literature as the benchmark. Because the available asset set to the investors in this paper is composed of component stocks in the corresponding stock index, it is reasonable to take the value-weighted or equal-weighted return of all these component stocks as the benchmark. Therefore, we make use of monthly return of stock index as the market proxy in Brazil, Russia and India, whilst the unavailability of Shanghai Stock Exchange 50 Index in China until 1 January 2004 drives us to the monthly return of the equal-weighted price across all existing component stocks. For risk-free return, we download from Datastream the middle rates of the savings account in Brazil, the interbank 8-to-30-day loan in Russia, the 91-day T-Bill in India and the 20-day relending rate in China.

In addition to the market factor proxy, size (price times shares) and book-to-market equity are also expected to be proxies for common risk factors in stock returns; and these common risk factors are documented to be related to economic fundamentals, see Fama and French (1992b). In line with Fama and French (1992b, 1993) we form six portfolios from sorting stocks by ME and book-to-market (BE/ME) in order to mimic the underlying risk factors: based on ME, we break all stocks in each stock market into two groups, the up 50% group (B) and the down 50% group (S); and we also rank all stocks in this market on BE/ME, and split them into three groups, the bottom 30% (L), middle 40% (M) and top 30% (H). These splits are arbitrary, but as Fama and French (1993) argue, there is no reason that their results are sensitive to these choices. The intersection of the ME and BE/ME grouping criteria gives us six portfolios: S/L, S/M, S/H, B/L, B/M and B/L. Each month, these portfolios are updated and their monthly returns are calculated. The difference between the simple averaged return on S/H and B/H portfolios and that on S/L and B/L portfolios is HML; and SMB is the difference between S and B portfolio returns. Also, we monthly rank all stocks on their prior 12-month return and construct the rolling momentum factor, Mom, as the value-weighted average return of the top 30% minus the value-weighted average return of the bottom 30%. We construct all these factors by using the online research tool of Style Research Ltd.

3.3. *Empirical results*

In our implementation, the trading results using recursive forecasts of the covariance matrix from a battery of conditional volatility and correlation models are presented and compared with the benchmarks. To study the cost effect on portfolio performance, we allow for three types of transaction cost patterns: no transaction cost at all as in a perfect market, low transaction cost of 0.5% on trading in shares, and high transaction cost of 1% on buying and selling stocks.

To save space, we did not report the results from Jensen's 1-factor regression and Fama and French's 3-factor regression, which are consistent but less comprehensive than the presented results from Carhart's 4-factor regression. They are available upon request from the authors. Under each of these three transaction cost scenarios, Panel A in Tables 2–3 presents some portfolio performance measures in Brazil, Russia, India and China, including the average of the realized monthly return (R), Sharpe ratio (S), the estimated intercept (alpha, which we also call Carhart's alpha below) and its *t*-statistic (t) in Carhart's 4-factor performance regression, which tests whether the portfolio outruns the benchmark; and under the same cost scenario and the same investment strategy, each column in Panel B of these two tables shows some descriptive statistics for these performance measures across the portfolios using conditional volatility and correlation models, including the maximum and minimum values, the 50% quantile and the percentage of outperformer compared with the benchmark. For R, the benchmark is the average of the market index's monthly return, which is 1.46, 3.49, 1.73 and 0.09% for Brazil, Russia, India and China, respectively, within their investment sample period; for S, the benchmark is the Sharpe ratio of the market index: 0.18 for Brazil, 0.33 for Russia, 0.18 for India and –0.03 for China; the benchmarks for alpha and *t*-statistic are 0 and 5% critical value. The investment strategy under consideration is the minimum variance portfolio.

Some common features on the empirical results are observed across the countries under study. No matter which transaction cost scenario is assumed, both maximum and minimum values of the averaged return are found in those underlying models; however, no model dominates or is dominated by other models. The models realizing the highest averaged mean and Sharpe ratio may come from the same model family but have different model parameters: for example, for portfolios without transaction cost in China, the MMA model with window length of 100 and smooth parameter of 0.90 has the averaged return of 2.26%, the highest among all models, but its Sharpe ratio is less than that of the MMA(150,0.90) model.

Not surprisingly, if net of transaction cost, we can always find ways to outrun the benchmark: Carhart's alpha for all four FDP models are significantly positive across all countries. For portfolios without cost, Carhart's alpha (and its *t*-statistic) for the FDP(1,1,1,1) model is 2.42 (3.54) in Brazil, 1.71 (1.87) in Russia, 1.08 (2.17) in India and 1.93 (3.26) in China. Transaction cost, however, drives the portfolio performance sharply lower: as the fixed rate of transaction cost increases, both absolute value of Carhart's alpha and its *t*-statistic decrease: the value of the corresponding variable with 0.5% transaction cost decreases to 2.08 (3.05) in Brazil, 1.47 (1.62) in Russia, 0.70 (1.39) in India and 1.42 (2.38) in China, two of which are not significant any more. No matter which statistic of max, min, median and per cent of outperformer we take into consideration, the

Table 2. Performance measures for the switching portfolios in Brazil and Russia.

Country		Brazil												Russia											
Transaction cost		Zero				Low				High				Zero				Low				High			
Performance measure		R	S	alpha	t	R	S	alpha	t	R	S	alpha	t	R	S	alpha	t	R	S	alpha	t	R	S	alpha	t
Panel A: Raw result																									
EQMA	100	2.51	0.33	1.80	2.38	0.97	0.13	0.30	0.40	−0.54	−0.08	−1.16	−1.53	2.07	0.20	0.19	0.15	1.44	0.14	−0.36	−0.29	0.82	0.08	−0.89	−0.74
	150	2.47	0.33	1.67	2.24	1.57	0.21	0.80	1.08	0.69	0.10	−0.04	−0.06	2.66	0.32	0.63	0.68	2.23	0.27	0.26	0.29	1.81	0.22	−0.10	−0.11
EWMA	(100,0.96,0.96)	2.03	0.24	1.44	1.64	−0.35	−0.04	−0.87	−0.99	−2.67	−0.33	−3.11	−3.55	1.91	0.17	−0.10	−0.07	1.06	0.10	−0.85	−0.63	0.22	0.02	−1.59	−1.19
	(100,0.96,0.94)	1.44	0.15	0.93	0.90	−1.68	−0.18	−2.09	−2.02	−4.72	−0.51	−5.03	−4.75	1.84	0.16	−0.16	−0.12	0.75	0.07	−1.16	−0.83	−0.33	−0.03	−2.13	−1.55
	(100,0.96,0.92)	1.12	0.11	0.60	0.51	−2.81	−0.27	−3.21	−2.68	−6.63	−0.62	−6.92	−5.61	1.87	0.16	−0.22	−0.15	0.44	0.04	−1.55	−1.08	−0.97	−0.08	−2.86	−2.00
	(100,0.96,0.90)	1.11	0.09	0.54	0.40	−3.60	−0.31	−4.05	−3.01	−8.19	−0.69	−8.52	−6.15	2.01	0.17	−0.20	−0.14	0.28	0.02	−1.85	−1.27	−1.43	−0.12	−3.48	−2.39
	(100,0.94,0.94)	1.67	0.18	1.12	1.10	−1.42	−0.15	−1.88	−1.85	−4.43	−0.48	−4.80	−4.63	1.83	0.16	−0.23	−0.16	0.77	0.07	−1.17	−0.83	−0.27	−0.02	−2.10	−1.50
	(100,0.94,0.92)	1.34	0.13	0.82	0.69	−2.53	−0.24	−2.93	−2.45	−6.29	−0.59	−6.59	−5.34	1.80	0.15	−0.34	−0.23	0.45	0.04	−1.58	−1.08	−0.89	−0.08	−2.80	−1.93
	(100,0.94,0.90)	1.34	0.11	0.78	0.58	−3.31	−0.28	−3.75	−2.75	−7.85	−0.65	−8.16	−5.81	1.86	0.15	−0.42	−0.28	0.22	0.02	−1.95	−1.31	−1.40	−0.12	−3.46	−2.33
MMA	(100,0.90)	0.42	0.04	−0.09	−0.07	−4.33	−0.39	−4.75	−3.68	−9.01	−0.79	−9.34	−6.95	2.40	0.22	0.51	0.37	0.53	0.05	−1.29	−0.95	−1.32	−0.12	−3.08	−2.27
	(150,0.90)	0.45	0.04	−0.06	−0.04	−4.34	−0.36	−4.77	−3.38	−9.08	−0.74	−9.41	−6.42	2.20	0.21	0.31	0.24	0.33	0.03	−1.48	−1.19	−1.52	−0.15	−3.25	−2.62
	(100,0.92)	0.55	0.05	0.06	0.05	−3.51	−0.33	−3.92	−3.24	−7.48	−0.70	−7.79	−6.25	2.05	0.19	0.28	0.21	0.51	0.05	−1.18	−0.88	−1.01	−0.09	−2.63	−1.96
	(150,0.92)	0.66	0.06	0.13	0.10	−3.39	−0.31	−3.83	−3.01	−7.35	−0.67	−7.69	−5.88	2.01	0.20	0.28	0.23	0.49	0.05	−1.16	−0.96	−1.02	−0.10	−2.58	−2.15
	(100,0.94)	0.98	0.10	0.50	0.46	−2.29	−0.24	−2.68	−2.47	−5.48	−0.57	−5.78	−5.21	1.86	0.18	0.14	0.11	0.68	0.06	−0.96	−0.74	−0.49	−0.05	−2.05	−1.58
	(100,0.94)	1.16	0.12	0.58	0.53	−2.02	−0.21	−2.49	−2.26	−5.11	−0.53	−5.49	−4.92	1.90	0.20	0.22	0.19	0.74	0.08	−0.85	−0.74	−0.41	−0.04	−1.90	−1.67
GEWMA	(100,1,1,0.94)	1.73	0.17	1.07	0.94	−1.69	−0.16	−2.30	−1.99	−5.01	−0.48	−5.58	−4.66	1.52	0.14	−0.19	−0.15	0.32	0.03	−1.29	−1.02	−0.85	−0.08	−2.37	−1.89
	(100,1,1,0.90)	1.17	0.09	0.63	0.42	−3.79	−0.28	−4.23	−2.71	−8.68	−0.63	−9.02	−5.53	1.70	0.15	−0.15	−0.11	−0.17	−0.02	−1.93	−1.43	−2.02	−0.18	−3.69	−2.73
	(100,1,2,0.94)	1.52	0.15	0.87	0.75	−1.90	−0.18	−2.51	−2.12	−5.23	−0.49	−5.79	−4.73	1.71	0.17	0.08	0.06	0.55	0.05	−1.01	−0.81	−0.60	−0.06	−2.08	−1.69
	(100,1,2,0.90)	0.73	0.05	0.23	0.15	−4.39	−0.32	−4.78	−2.94	−9.50	−0.66	−9.74	−5.70	1.85	0.17	0.07	0.05	0.02	0.00	−1.68	−1.26	−1.80	−0.17	−3.41	−2.55
	(100,2,1,0.94)	1.71	0.17	1.06	0.97	−1.72	−0.17	−2.31	−2.07	−5.05	−0.50	−5.61	−4.83	2.01	0.22	0.16	0.16	0.81	0.09	−0.94	−0.94	−0.37	−0.04	−2.02	−2.00
	(100,2,1,0.90)	1.22	0.10	0.76	0.53	−3.86	−0.30	−4.23	−2.82	−8.87	−0.67	−9.13	−5.79	2.10	0.21	0.06	0.05	0.21	0.02	−1.75	−1.49	−1.66	−0.17	−3.53	−2.98
	(100,2,2,0.94)	1.86	0.19	1.21	1.09	−1.63	−0.16	−2.23	−1.96	−5.03	−0.48	−5.60	−4.74	1.87	0.18	0.26	0.20	0.72	0.07	−0.82	−0.66	−0.42	−0.04	−1.88	−1.54
	(100,2,2,0.90)	1.41	0.11	0.90	0.60	−3.75	−0.29	−4.18	−2.72	−8.85	−0.65	−9.17	−5.70	2.03	0.18	0.31	0.23	0.21	0.02	−1.46	−1.10	−1.59	−0.15	−3.19	−2.41
CCC	(1,1)	3.28	0.48	2.45	3.91	2.23	0.33	1.45	2.33	1.21	0.18	0.46	0.75	2.42	0.26	0.59	0.54	1.96	0.21	0.16	0.15	1.50	0.16	−0.27	−0.25
	(1,2)	3.19	0.47	2.38	3.79	2.12	0.32	1.35	2.16	1.07	0.16	0.34	0.54	3.02	0.38	1.05	1.36	2.54	0.32	0.61	0.79	2.07	0.27	0.18	0.23
	(2,1)	3.18	0.47	2.37	3.81	2.11	0.32	1.34	2.17	1.05	0.16	0.33	0.53	3.03	0.38	1.05	1.32	2.56	0.32	0.62	0.78	2.09	0.27	0.20	0.25
	(2,2)	3.19	0.47	2.39	3.84	2.08	0.31	1.31	2.11	0.99	0.15	0.26	0.41	2.49	0.26	0.72	0.66	2.03	0.22	0.29	0.27	1.57	0.17	−0.13	−0.12
BEKK	(1,1)	2.83	0.44	2.10	3.43	2.44	0.38	1.74	2.87	2.07	0.33	1.39	2.30	3.63	0.46	1.97	2.35	3.38	0.43	1.75	2.10	3.13	0.40	1.54	1.85
	(1,2)	2.84	0.44	2.11	3.43	2.45	0.38	1.74	2.87	2.06	0.33	1.39	2.30	3.62	0.46	1.96	2.35	3.37	0.43	1.74	2.09	3.12	0.40	1.53	1.84
	(2,1)	2.83	0.44	2.11	3.43	2.45	0.38	1.74	2.87	2.07	0.33	1.39	2.31	3.64	0.46	1.98	2.37	3.39	0.43	1.76	2.12	3.14	0.41	1.55	1.86
	(2,2)	2.84	0.44	2.11	3.43	2.45	0.38	1.74	2.87	2.07	0.33	1.39	2.30	3.62	0.46	1.97	2.36	3.37	0.43	1.75	2.10	3.12	0.40	1.54	1.85
DCC	(1,1,1,1)	3.27	0.48	2.44	3.89	2.23	0.33	1.44	2.32	1.21	0.18	0.46	0.74	2.43	0.26	0.58	0.53	1.97	0.21	0.15	0.14	1.52	0.16	−0.27	−0.26
	(1,2,1,1)	3.19	0.47	2.38	3.79	2.12	0.32	1.35	2.16	1.07	0.16	0.33	0.54	3.03	0.38	1.03	1.34	2.55	0.32	0.60	0.78	2.08	0.27	0.16	0.21
	(2,1,1,1)	3.17	0.47	2.37	3.80	2.10	0.32	1.34	2.16	1.05	0.16	0.33	0.53	3.03	0.38	1.04	1.31	2.56	0.32	0.61	0.77	2.10	0.27	0.19	0.23
	(2,2,1,1)	3.19	0.47	2.38	3.84	2.08	0.31	1.31	2.11	0.99	0.15	0.25	0.40	2.50	0.26	0.71	0.65	2.03	0.22	0.28	0.26	1.57	0.17	−0.14	−0.13
OGARCH	(1,1,1,1)	2.77	0.43	2.04	3.29	2.34	0.37	1.63	2.64	1.91	0.30	1.22	1.98	3.68	0.46	1.94	2.24	3.37	0.42	1.66	1.92	3.07	0.39	1.39	1.61
Shrinkage		2.79	0.43	2.07	3.41	2.54	0.40	1.84	3.07	2.29	0.37	1.62	2.71	3.65	0.46	1.99	2.38	3.47	0.45	1.85	2.21	3.29	0.43	1.70	2.04
FDP	(1,1,1,1)	3.18	0.45	2.42	3.54	2.81	0.40	2.08	3.05	2.46	0.36	1.74	2.57	3.58	0.42	1.71	1.87	3.31	0.39	1.47	1.62	3.04	0.36	1.24	1.37
	(1,2,1,1)	3.17	0.45	2.41	3.54	2.81	0.40	2.07	3.06	2.46	0.36	1.74	2.57	3.60	0.42	1.72	1.86	3.32	0.39	1.48	1.61	3.05	0.36	1.25	1.36
	(2,1,1,1)	3.18	0.45	2.42	3.51	2.81	0.40	2.08	3.02	2.45	0.35	1.74	2.54	3.58	0.42	1.71	1.88	3.31	0.39	1.47	1.62	3.03	0.36	1.24	1.37
	(2,2,1,1)	3.17	0.45	2.42	3.52	2.81	0.40	2.07	3.03	2.44	0.36	1.73	2.54	3.60	0.42	1.72	1.86	3.32	0.39	1.47	1.61	3.05	0.36	1.24	1.35

(*continued*)

Table 2. (*Continued*).

Country		Brazil												Russia											
Transaction cost		Zero				Low				High				Zero				Low				High			
Performance measure		R	S	alpha	t	R	S	alpha	t	R	S	alpha	t	R	S	alpha	t	R	S	alpha	t	R	S	alpha	t
SCCC	(1,1)	2.61	0.36	2.02	2.92	0.44	0.06	−0.13	−0.19	−1.70	−0.24	−2.24	−3.10	3.98	0.44	1.62	1.61	2.98	0.34	0.71	0.72	1.99	0.23	−0.19	−0.20
	(1,2)	2.60	0.38	2.01	3.18	1.30	0.20	0.72	1.15	0.02	0.00	−0.55	−0.87	4.04	0.50	1.94	2.26	3.29	0.41	1.23	1.45	2.55	0.32	0.54	0.63
	(2,1)	2.57	0.39	1.89	3.04	1.83	0.28	1.17	1.89	1.10	0.17	0.45	0.74	3.86	0.49	1.99	2.43	3.40	0.44	1.59	1.95	2.96	0.39	1.19	1.46
	(2,2)	2.62	0.36	2.05	2.97	0.46	0.07	−0.08	−0.11	−1.66	−0.23	−2.17	−3.05	3.99	0.44	1.63	1.60	3.00	0.34	0.73	0.74	2.03	0.23	−0.15	−0.16
SBEKK	(1,1)	2.61	0.39	2.03	3.21	1.33	0.20	0.76	1.22	0.07	0.01	−0.50	−0.79	3.97	0.49	1.89	2.22	3.23	0.40	1.20	1.40	2.50	0.31	0.51	0.58
	(1,2)	2.55	0.39	1.88	3.02	1.83	0.28	1.18	1.93	1.13	0.18	0.50	0.82	3.82	0.49	1.98	2.42	3.40	0.44	1.60	1.97	2.99	0.39	1.23	1.51
	(2,1)	2.86	0.38	2.24	3.09	0.68	0.09	0.08	0.11	−1.47	−0.20	−2.04	−2.79	3.34	0.33	0.95	0.81	2.32	0.23	0.03	0.03	1.32	0.13	−0.88	−0.77
	(2,2)	2.66	0.38	2.06	3.12	1.33	0.19	0.73	1.12	0.03	0.00	−0.57	−0.86	3.61	0.41	1.51	1.53	2.83	0.32	0.77	0.79	2.06	0.23	0.04	0.04
SDCC	(1,1,1,1)	2.70	0.40	2.02	3.16	1.86	0.28	1.19	1.87	1.03	0.16	0.37	0.59	3.59	0.43	1.65	1.84	3.11	0.38	1.21	1.36	2.63	0.32	0.77	0.87
	(1,2,1,1)	2.85	0.38	2.23	3.09	0.67	0.09	0.07	0.10	−1.47	−0.20	−2.05	−2.80	3.32	0.32	0.93	0.79	2.31	0.23	0.01	0.01	1.31	0.13	−0.90	−0.78
	(2,1,1,1)	2.66	0.38	2.05	3.12	1.33	0.19	0.73	1.12	0.03	0.00	−0.57	−0.86	3.58	0.40	1.47	1.48	2.81	0.31	0.74	0.75	2.04	0.23	0.01	0.01
	(2,2,1,1)	2.70	0.40	2.02	3.15	1.85	0.28	1.18	1.87	1.03	0.16	0.37	0.59	3.56	0.42	1.63	1.79	3.08	0.37	1.19	1.31	2.61	0.31	0.75	0.84
SOGARCH	(1,1,1,1)	2.61	0.36	2.02	2.92	0.44	0.06	−0.14	−0.20	−1.70	−0.24	−2.25	−3.11	3.96	0.43	1.59	1.57	2.96	0.33	0.68	0.69	1.97	0.23	−0.22	−0.23
SShrinkage		2.60	0.38	2.01	3.18	1.30	0.20	0.72	1.15	0.02	0.00	−0.55	−0.87	4.02	0.49	1.90	2.21	3.27	0.40	1.19	1.40	2.53	0.31	0.50	0.59
SFDP	(1,1,1,1)	2.57	0.39	1.89	3.04	1.83	0.28	1.16	1.89	1.10	0.17	0.45	0.74	3.84	0.49	1.97	2.40	3.39	0.44	1.56	1.92	2.94	0.38	1.17	1.43
	(1,2,1,1)	2.61	0.36	2.02	2.92	0.44	0.06	−0.14	−0.20	−1.70	−0.24	−2.25	−3.11	3.96	0.43	1.60	1.57	2.95	0.33	0.68	0.69	1.96	0.22	−0.22	−0.23
	(2,1,1,1)	2.61	0.39	2.01	3.19	1.31	0.20	0.72	1.16	0.03	0.00	−0.55	−0.87	4.02	0.49	1.90	2.21	3.26	0.40	1.20	1.41	2.52	0.31	0.50	0.59
	(2,2,1,1)	2.58	0.39	1.89	3.04	1.83	0.28	1.17	1.90	1.10	0.17	0.45	0.74	3.84	0.49	1.97	2.40	3.39	0.44	1.56	1.92	2.94	0.38	1.17	1.44
Eweight		2.81	0.43	2.19	3.46	1.95	0.31	1.35	2.14	1.11	0.18	0.53	0.84	3.42	0.42	1.49	1.75	2.97	0.37	1.09	1.29	2.53	0.32	0.69	0.82
Thick	AIC best 15%	2.64	0.40	1.93	3.03	1.78	0.28	0.58	0.92	0.95	0.15	−0.74	−1.16	3.90	0.51	1.97	2.34	3.40	0.45	1.30	1.56	2.92	0.39	0.64	0.77
	SIC best 15%	2.64	0.41	1.93	3.03	1.77	0.28	0.58	0.92	0.93	0.15	−0.74	−1.16	3.88	0.51	2.00	2.39	3.38	0.45	1.35	1.63	2.90	0.39	0.71	0.86
Thick	AIC best 25%	2.62	0.36	1.99	3.29	0.46	0.07	1.16	1.94	−1.66	−0.23	0.34	0.57	3.99	0.44	2.00	2.48	3.00	0.34	1.54	1.93	2.03	0.23	1.10	1.38
	SIC best 25%	2.62	0.36	2.00	3.29	0.46	0.07	1.16	1.93	−1.66	−0.23	0.33	0.55	3.99	0.44	2.00	2.49	3.00	0.34	1.55	1.94	2.03	0.23	1.10	1.38
Thick	AIC best 50%	2.52	0.37	2.07	3.40	1.16	0.17	1.43	2.38	−0.17	−0.03	0.80	1.35	4.02	0.51	1.84	2.25	3.30	0.42	1.47	1.80	2.60	0.33	1.10	1.36
	SIC best 50%	2.52	0.37	2.09	3.37	1.16	0.17	1.27	2.07	−0.17	−0.03	0.47	0.76	4.02	0.51	1.82	2.20	3.32	0.43	1.41	1.72	2.64	0.34	1.01	1.24
BMA	AIC	2.71	0.42	2.05	2.97	2.05	0.32	−0.08	−0.11	1.41	0.23	−2.17	−3.05	3.71	0.48	1.63	1.60	3.30	0.43	0.73	0.74	2.89	0.38	−0.15	−0.16
	SIC	2.70	0.42	2.05	2.97	1.86	0.30	−0.08	−0.11	1.03	0.17	−2.17	−3.05	3.67	0.47	1.63	1.60	3.21	0.42	0.73	0.74	2.76	0.37	−0.15	−0.16
Panel B: Descriptive statistics																									
Max		3.28	0.48	2.45	3.91	2.81	0.40	2.08	3.07	2.46	0.37	1.74	2.71	4.04	0.51	2.00	2.49	3.47	0.45	1.85	2.21	3.29	0.43	1.70	2.04
Min		0.42	0.04	−0.09	−0.07	−4.39	−0.39	−4.78	−3.68	−9.50	−0.79	−9.74	−6.95	1.52	0.14	−0.42	−0.28	−0.17	−0.02	−1.95	−1.49	−2.02	−0.18	−3.69	−2.98
Median		2.61	0.38	2.02	3.04	1.31	0.20	0.72	1.12	0.03	0.00	−0.56	−0.87	3.49	0.41	1.48	1.51	2.82	0.32	0.68	0.74	2.03	0.23	−0.12	−0.12
Per cent of outperformer		0.78	0.74	0.97	0.69	0.44	0.53	0.60	0.43	0.15	0.22	0.43	0.15	0.50	0.57	0.87	0.40	0.00	0.46	0.68	0.21	0.00	0.28	0.49	0.07

Note: Panel A reports the performance of the portfolio using volatility and correlation models, where R is the averaged monthly return, S is Sharpe ratio, alpha is the estimated intercept in Carhart's 4-factor regression and t is the *t*-statistic of alpha. For each portfolio, three cost scenarios of zero (0% of trading), low (0.5% of trading) and high (1% of trading) are simulated for real-time transaction cost. The first capital S in SCC, SBEKK, SDCC, SOGARCH, SShrinkage and SFDP means semiparametric. Investors start off with 1 billion units of local currency at the beginning of the sample period and reinvest the portfolio income every month. As the investment starts on 1 January 2001 and ends on 31 December 2006, the risk-free return is sampled within this period for calculating Sharpe ratio. Panel B presents the descriptive statistics of strategy performances across the volatility and correlation models: max, min and median are standard statistics, and per cent of outperformer is the percentage of models performing better than the benchmarks: which is the averaged monthly market return for R, Sharpe ratio of the market return for S, the value of zero for alpha and the 5% critical value for t.

Table 3. Performance measures for the switching portfolios in India and China.

Country		India												China											
Transaction cost		Zero				Low				High				Zero				Low				High			
Performance measure		R	S	alpha	t	R	S	alpha	t	R	S	alpha	t	R	S	alpha	t	R	S	alpha	t	R	S	alpha	t
Panel A: Raw result																									
EQMA	100	2.56	0.40	1.56	3.45	1.94	0.31	0.96	2.15	1.33	0.22	0.38	0.84	1.14	0.17	1.22	1.74	0.31	0.05	0.36	0.52	−0.51	−0.08	−0.49	−0.70
	150	2.69	0.42	1.62	3.78	2.26	0.36	1.21	2.82	1.83	0.30	0.80	1.86	0.78	0.12	0.98	1.54	0.19	0.03	0.37	0.59	−0.39	−0.06	−0.22	−0.35
EWMA	(100,0.96,0.96)	2.33	0.34	1.13	2.29	1.29	0.19	0.10	0.19	0.27	0.04	−0.91	−1.69	1.12	0.15	1.23	1.57	−0.26	−0.04	−0.22	−0.27	−1.61	−0.22	−1.64	−1.96
	(100,0.96,0.94)	2.19	0.29	0.93	1.55	0.79	0.11	−0.47	−0.75	−0.59	−0.08	−1.84	−2.76	1.36	0.18	1.42	1.72	−0.45	−0.06	−0.49	−0.57	−2.23	−0.29	−2.35	−2.58
	(100,0.96,0.92)	2.21	0.27	0.91	1.26	0.40	0.05	−0.90	−1.18	−1.39	−0.16	−2.69	−3.30	1.63	0.21	1.63	1.88	−0.68	−0.09	−0.79	−0.87	−2.95	−0.36	−3.16	−3.19
	(100,0.96,0.90)	2.37	0.26	1.05	1.24	0.15	0.02	−1.17	−1.32	−2.05	−0.22	−3.36	−3.57	1.83	0.23	1.79	1.92	−0.99	−0.12	−1.15	−1.18	−3.75	−0.42	−4.04	−3.74
	(100,0.94,0.94)	2.28	0.31	0.96	1.73	0.90	0.12	−0.41	−0.70	−0.46	−0.06	−1.76	−2.83	1.15	0.16	1.30	1.61	−0.65	−0.09	−0.59	−0.70	−2.42	−0.32	−2.44	−2.74
	(100,0.94,0.92)	2.29	0.28	0.92	1.36	0.52	0.06	−0.84	−1.19	−1.23	−0.15	−2.58	−3.40	1.41	0.19	1.52	1.78	−0.86	−0.11	−0.86	−0.96	−3.08	−0.38	−3.19	−3.30
	(100,0.94,0.90)	2.42	0.27	1.03	1.30	0.25	0.03	−1.13	−1.37	−1.88	−0.21	−3.26	−3.70	1.59	0.20	1.67	1.83	−1.17	−0.14	−1.22	−1.26	−3.88	−0.44	−4.06	−3.81
MMA	(100,0.90)	2.03	0.21	0.80	0.81	−0.33	−0.03	−1.57	−1.51	−2.66	−0.26	−3.90	−3.51	2.26	0.26	2.01	2.07	−0.58	−0.07	−0.92	−0.92	−3.35	−0.37	−3.78	−3.48
	(150,0.90)	2.00	0.20	0.70	0.70	−0.39	−0.04	−1.68	−1.57	−2.74	−0.25	−4.02	−3.50	2.18	0.28	2.06	2.30	−0.73	−0.09	−0.97	−1.03	−3.57	−0.42	−3.93	−3.81
	(100,0.92)	1.89	0.21	0.67	0.78	−0.03	0.00	−1.25	−1.37	−1.92	−0.20	−3.14	−3.21	2.01	0.25	1.79	1.96	−0.37	−0.04	−0.67	−0.71	−2.69	−0.32	−3.08	−3.02
	(150,0.92)	1.93	0.21	0.68	0.78	0.01	0.00	−1.23	−1.32	−1.89	−0.20	−3.11	−3.12	1.90	0.26	1.82	2.18	−0.52	−0.07	−0.70	−0.80	−2.89	−0.36	−3.17	−3.32
	(100,0.94)	1.86	0.23	0.68	0.94	0.39	0.05	−0.78	−1.01	−1.05	−0.13	−2.22	−2.71	1.71	0.22	1.54	1.80	−0.19	−0.02	−0.43	−0.48	−2.04	−0.25	−2.36	−2.52
	(100,0.94)	1.96	0.24	0.79	1.09	0.51	0.06	−0.65	−0.84	−0.91	−0.11	−2.06	−2.52	1.56	0.21	1.53	1.92	−0.35	−0.05	−0.46	−0.56	−2.21	−0.30	−2.40	−2.75
GEWMA	(100,1,1,0.94)	2.25	0.29	0.99	1.58	0.88	0.11	−0.34	−0.53	−0.48	−0.06	−1.65	−2.50	1.39	0.19	1.57	1.98	−0.61	−0.08	−0.49	−0.59	−2.57	−0.33	−2.51	−2.85
	(100,1,1,0.90)	2.46	0.28	1.13	1.42	0.38	0.04	−0.93	−1.13	−1.68	−0.19	−2.95	−3.41	1.83	0.23	1.82	2.02	−1.10	−0.14	−1.18	−1.23	−3.95	−0.45	−4.10	−3.91
	(100,1,2,0.94)	2.46	0.31	1.30	2.03	1.07	0.14	−0.05	−0.07	−0.30	−0.04	−1.37	−2.05	1.39	0.19	1.56	1.99	−0.65	−0.09	−0.53	−0.64	−2.65	−0.34	−2.58	−2.91
	(100,1,2,0.90)	2.71	0.31	1.46	1.86	0.61	0.07	−0.60	−0.74	−1.47	−0.17	−2.64	−3.07	1.72	0.21	1.71	1.82	−1.26	−0.14	−1.31	−1.28	−4.16	−0.44	−4.24	−3.77
	(100,2,1,0.94)	2.17	0.28	0.92	1.43	0.78	0.10	−0.42	−0.64	−0.59	−0.08	−1.75	−2.56	1.04	0.14	1.20	1.47	−0.97	−0.13	−0.89	−1.04	−2.94	−0.37	−2.94	−3.23
	(100,2,1,0.90)	2.34	0.26	1.02	1.25	0.25	0.03	−1.02	−1.21	−1.82	−0.20	−3.04	−3.40	1.39	0.17	1.38	1.44	−1.59	−0.18	−1.68	−1.63	−4.49	−0.47	−4.66	−4.11
	(100,2,2,0.94)	2.37	0.30	1.20	1.83	0.97	0.13	−0.15	−0.23	−0.40	−0.05	−1.48	−2.16	0.99	0.13	1.16	1.46	−1.06	−0.14	−0.97	−1.16	−3.08	−0.39	−3.05	−3.44
	(100,2,2,0.90)	2.58	0.29	1.35	1.66	0.47	0.05	−0.71	−0.84	−1.60	−0.18	−2.74	−3.06	1.36	0.16	1.38	1.46	−1.66	−0.19	−1.71	−1.69	−4.59	−0.50	−4.71	−4.26
CCC	(1,1)	2.59	0.39	1.35	3.31	1.90	0.29	0.68	1.67	1.22	0.19	0.01	0.02	0.75	0.11	1.11	1.73	−0.29	−0.04	0.05	0.08	−1.31	−0.19	−0.99	−1.56
	(1,2)	2.70	0.40	1.45	3.55	2.00	0.30	0.77	1.89	1.31	0.20	0.10	0.24	0.56	0.08	0.86	1.35	−0.47	−0.07	−0.18	−0.28	−1.47	−0.22	−1.21	−1.91
	(2,1)	2.70	0.40	1.53	3.67	1.99	0.30	0.84	2.04	1.30	0.20	0.16	0.39	0.67	0.10	1.02	1.66	−0.38	−0.06	−0.06	−0.09	−1.42	−0.21	−1.12	−1.84
	(2,2)	2.80	0.41	1.60	3.82	2.08	0.31	0.90	2.16	1.37	0.21	0.20	0.50	0.47	0.07	0.80	1.30	−0.59	−0.09	−0.28	−0.46	−1.63	−0.24	−1.33	−2.20
BEKK	(1,1)	2.64	0.41	1.43	3.71	2.33	0.37	1.15	2.99	2.03	0.33	0.87	2.26	1.18	0.19	1.40	2.72	0.72	0.12	0.93	1.83	0.28	0.05	0.47	0.93
	(1,2)	2.63	0.41	1.43	3.69	2.32	0.37	1.14	2.97	2.02	0.32	0.86	2.24	1.19	0.19	1.40	2.73	0.73	0.12	0.94	1.83	0.29	0.05	0.48	0.94
	(2,1)	2.64	0.41	1.44	3.71	2.34	0.37	1.16	3.00	2.04	0.33	0.88	2.28	1.17	0.18	1.40	2.73	0.72	0.12	0.94	1.84	0.27	0.05	0.48	0.95
	(2,2)	2.63	0.41	1.43	3.70	2.32	0.37	1.14	2.97	2.02	0.32	0.86	2.24	1.18	0.19	1.38	2.68	0.74	0.12	0.93	1.81	0.31	0.05	0.49	0.95
DCC	(1,1,1,1)	2.61	0.39	1.38	3.36	1.92	0.29	0.70	1.73	1.24	0.19	0.04	0.09	0.82	0.12	1.22	1.94	−0.21	−0.03	0.17	0.27	−1.22	−0.18	−0.86	−1.38
	(1,2,1,1)	2.72	0.41	1.48	3.60	2.02	0.31	0.80	1.96	1.33	0.21	0.12	0.31	0.59	0.09	0.94	1.49	−0.42	−0.06	−0.10	−0.15	−1.42	−0.21	−1.11	−1.78
	(2,1,1,1)	2.72	0.40	1.56	3.72	2.02	0.31	0.87	2.09	1.32	0.20	0.19	0.46	0.73	0.11	1.12	1.87	−0.31	−0.05	0.05	0.09	−1.34	−0.20	−1.00	−1.67
	(2,2,1,1)	2.82	0.42	1.63	3.86	2.10	0.32	0.93	2.22	1.40	0.22	0.23	0.56	0.51	0.07	0.87	1.45	−0.54	−0.08	−0.19	−0.32	−1.57	−0.24	−1.24	−2.07
OGARCH	(1,1,1,1)	2.63	0.41	1.39	3.75	2.26	0.36	1.04	2.80	1.90	0.30	0.69	1.84	1.13	0.18	1.42	2.63	0.59	0.09	0.88	1.54	0.06	0.01	0.33	0.56
Shrinkage		2.64	0.41	1.41	3.61	2.45	0.38	1.24	3.20	2.26	0.36	1.07	2.79	1.37	0.22	1.58	3.37	1.14	0.19	1.34	2.87	0.92	0.16	1.11	2.37
FDP	(1,1,1,1)	2.41	0.36	1.08	2.17	2.02	0.30	0.70	1.39	1.63	0.25	0.32	0.63	1.58	0.24	1.93	3.26	1.05	0.16	1.42	2.38	0.53	0.08	0.92	1.51
	(1,2,1,1)	2.43	0.36	1.10	2.18	2.03	0.31	0.71	1.40	1.64	0.25	0.33	0.64	1.58	0.23	1.89	3.15	1.04	0.16	1.36	2.23	0.51	0.08	0.83	1.34
	(2,1,1,1)	2.40	0.36	1.07	2.16	2.01	0.30	0.69	1.37	1.62	0.24	0.31	0.61	1.59	0.24	1.94	3.28	1.06	0.16	1.43	2.39	0.53	0.08	0.92	1.52
	(2,2,1,1)	2.43	0.36	1.10	2.20	2.03	0.31	0.71	1.41	1.64	0.25	0.33	0.65	1.56	0.23	1.88	3.14	1.02	0.15	1.33	2.19	0.49	0.07	0.79	1.28

(*continued*)

Table 3. (*Continued*).

Country		India												China											
Transaction cost		Zero				Low				High				Zero				Low				High			
Performance measure		R	S	alpha	t	R	S	alpha	t	R	S	alpha	t	R	S	alpha	t	R	S	alpha	t	R	S	alpha	t
SCCC	(1,1)	1.91	0.22	0.59	0.71	0.39	0.04	−0.85	−0.91	−1.11	−0.11	−2.29	−2.09	1.43	0.18	1.58	2.31	−0.43	−0.05	−0.42	−0.52	−2.26	−0.25	−2.39	−2.40
	(1,2)	2.18	0.31	0.96	1.90	1.21	0.17	−0.02	−0.05	0.25	0.03	−1.00	−1.82	0.75	0.11	1.01	1.56	−0.34	−0.05	−0.12	−0.17	−1.40	−0.19	−1.24	−1.51
	(2,1)	2.16	0.32	0.92	2.31	1.58	0.24	0.34	0.85	1.00	0.15	−0.23	−0.54	1.12	0.18	1.39	2.88	0.39	0.06	0.63	1.23	−0.33	−0.05	−0.13	−0.24
	(2,2)	2.08	0.24	0.77	0.92	0.64	0.07	−0.59	−0.66	−0.79	−0.08	−1.94	−1.94	1.55	0.21	1.72	2.72	−0.28	−0.04	−0.23	−0.31	−2.08	−0.26	−2.15	−2.44
SBEKK	(1,1)	2.30	0.32	1.05	1.95	1.35	0.19	0.11	0.20	0.42	0.06	−0.82	−1.46	0.97	0.15	1.29	2.16	−0.03	0.00	0.24	0.37	−1.02	−0.15	−0.79	−1.07
	(1,2)	2.32	0.34	1.08	2.59	1.75	0.26	0.53	1.29	1.20	0.18	−0.03	−0.06	1.29	0.21	1.58	3.38	0.68	0.12	0.93	1.94	0.08	0.01	0.30	0.59
	(2,1)	2.33	0.28	1.02	1.29	0.80	0.09	−0.46	−0.58	−0.72	−0.08	−1.93	−2.21	2.09	0.25	2.62	3.59	0.19	0.02	0.62	0.79	−1.67	−0.19	−1.34	−1.42
	(2,2)	2.58	0.34	1.50	2.45	1.39	0.19	0.24	0.45	0.22	0.03	−1.01	−1.74	0.97	0.13	1.45	2.12	−0.33	−0.04	0.13	0.16	−1.60	−0.19	−1.18	−1.20
SDCC	(1,1,1,1)	2.34	0.35	1.17	2.71	1.61	0.24	0.43	1.02	0.89	0.13	−0.30	−0.69	1.26	0.20	1.72	3.19	0.41	0.06	0.86	1.48	−0.43	−0.06	0.02	0.03
	(1,2,1,1)	2.37	0.28	1.05	1.31	0.83	0.10	−0.44	−0.54	−0.69	−0.08	−1.92	−2.17	2.09	0.25	2.57	3.41	0.17	0.02	0.54	0.67	−1.71	−0.19	−1.46	−1.51
	(2,1,1,1)	2.59	0.34	1.50	2.46	1.41	0.20	0.25	0.46	0.24	0.03	−0.99	−1.69	0.94	0.13	1.38	1.98	−0.37	−0.05	0.03	0.04	−1.66	−0.19	−1.30	−1.31
	(2,2,1,1)	2.36	0.35	1.18	2.69	1.63	0.24	0.44	1.03	0.91	0.13	−0.30	−0.68	1.19	0.18	1.61	2.84	0.32	0.05	0.72	1.16	−0.54	−0.08	−0.15	−0.22
SOGARCH	(1,1,1,1)	2.09	0.24	0.75	0.90	0.57	0.06	−0.71	−0.76	−0.94	−0.09	−2.15	−1.97	1.44	0.19	1.58	2.31	−0.41	−0.05	−0.41	−0.51	−2.25	−0.25	−2.38	−2.40
SShrinkage		2.22	0.31	0.99	1.96	1.24	0.18	0.00	0.00	0.28	0.04	−0.97	−1.78	0.76	0.11	1.02	1.57	−0.31	−0.04	−0.11	−0.15	−1.38	−0.18	−1.22	−1.49
SFDP	(1,1,1,1)	2.17	0.32	0.92	2.31	1.58	0.24	0.34	0.84	1.00	0.15	−0.23	−0.55	1.13	0.18	1.40	2.87	0.41	0.07	0.63	1.23	−0.31	−0.05	−0.12	−0.22
	(1,2,1,1)	2.06	0.23	0.72	0.85	0.52	0.05	−0.75	−0.78	−1.00	−0.09	−2.20	−1.95	1.45	0.19	1.58	2.31	−0.39	−0.05	−0.39	−0.48	−2.21	−0.25	−2.33	−2.41
	(2,1,1,1)	2.19	0.31	0.96	1.94	1.22	0.17	−0.02	−0.04	0.26	0.04	−0.99	−1.83	0.78	0.11	1.03	1.59	−0.30	−0.04	−0.10	−0.14	−1.37	−0.18	−1.22	−1.49
	(2,2,1,1)	2.13	0.32	0.88	2.20	1.54	0.23	0.30	0.73	0.96	0.14	−0.28	−0.64	1.12	0.18	1.38	2.82	0.40	0.07	0.61	1.18	−0.32	−0.05	−0.14	−0.25
Eweight		2.32	0.35	1.10	2.68	1.72	0.26	0.52	1.26	1.13	0.17	−0.05	−0.13	1.13	0.18	1.43	2.60	0.38	0.06	0.66	1.19	−0.35	−0.06	−0.10	−0.18
Thick	AIC best 15%	2.26	0.33	0.85	1.70	1.68	0.25	−0.06	−0.13	1.11	0.17	−0.97	−1.90	1.29	0.20	1.43	2.78	0.55	0.09	0.29	0.53	−0.17	−0.03	−0.84	−1.44
	SIC best 15%	2.26	0.34	0.92	2.10	1.69	0.26	0.25	0.57	1.14	0.17	−0.41	−0.93	1.33	0.21	1.32	2.38	0.58	0.09	0.25	0.42	−0.15	−0.03	−0.81	−1.30
Thick	AIC best 25%	2.08	0.24	0.98	2.35	0.64	0.07	0.42	1.01	−0.79	−0.08	−0.13	−0.32	1.55	0.21	1.52	3.16	−0.28	−0.04	0.76	1.55	−2.08	−0.26	0.01	0.01
	SIC best 25%	2.08	0.24	1.00	2.42	0.64	0.07	0.45	1.10	−0.79	−0.08	−0.08	−0.20	1.55	0.21	1.54	3.09	−0.28	−0.04	0.76	1.51	−2.08	−0.26	0.00	−0.01
Thick	AIC best 50%	2.14	0.30	0.99	2.46	1.22	0.17	0.43	1.08	0.31	0.04	−0.11	−0.27	1.19	0.18	1.47	2.76	0.10	0.01	0.74	1.38	−0.98	−0.15	0.03	0.05
	SIC best 50%	2.18	0.32	1.02	2.51	1.49	0.22	0.44	1.08	0.82	0.12	−0.13	−0.30	1.12	0.17	1.32	2.45	0.09	0.01	0.52	0.96	−0.93	−0.14	−0.27	−0.48
BMA	AIC	2.22	0.33	0.77	0.92	1.65	0.25	−0.59	−0.66	1.09	0.17	−1.94	−1.94	1.27	0.19	1.72	2.72	0.57	0.09	−0.23	−0.31	−0.12	−0.02	−2.15	−2.44
	SIC	2.24	0.34	0.77	0.92	1.65	0.25	−0.59	−0.66	1.06	0.16	−1.94	−1.94	1.17	0.18	1.72	2.72	0.40	0.06	−0.23	−0.31	−0.36	−0.06	−2.15	−2.44
Panel B: Descriptive statistics																									
Max		2.82	0.42	1.63	3.86	2.45	0.38	1.24	3.20	2.26	0.36	1.07	2.79	2.26	0.28	2.62	3.59	1.14	0.19	1.43	2.87	0.92	0.16	1.11	2.37
Min		1.86	0.20	0.59	0.70	−0.39	−0.04	−1.68	−1.57	−2.74	−0.26	−4.02	−3.70	0.47	0.07	0.80	1.30	−1.66	−0.19	−1.71	−1.69	−4.59	−0.50	−4.71	−4.26
Median		2.33	0.32	1.05	2.13	1.37	0.19	0.18	0.33	0.30	0.04	−0.94	−1.69	1.27	0.19	1.44	2.14	−0.29	−0.04	−0.08	−0.12	−1.45	−0.19	−1.22	−1.54
Per cent of outperformer		1.00	1.00	1.00	0.66	0.31	0.53	0.53	0.24	0.10	0.29	0.29	0.10	1.00	1.00	1.00	0.79	0.38	0.43	0.49	0.15	0.13	0.18	0.21	0.01

Note: See the note to Table 2 for details. The investment period in China is 1 January 2000–31 December 2005.

same unambiguous decreasing trend is also observed among the descriptive statistics in Panel B of both Tables 2 and 3 as the erosion of transaction cost on portfolio return gets more and more severe: for instance, in China, as the transaction cost increases from 0 to 0.5 to 1%, per cent of outperformer in forms of averaged return decreases from 1.00 to 0.38 and further down to 0.13; the percentage of those positive intercepts (t-statistic bigger than 5% critical value) in Carhart's performance regressions changes from 1.00 (0.79), to 0.49 (0.15), to 0.21 (0.01) following the increase of transaction cost. An argument is the fact that we do not consider transaction cost when we calculate factors for all performance measures somewhat makes comparison unfair.

The shrinkage model is the 'super-star' in our study, which obtains outrunning-the-benchmark performance across the countries, across the transaction cost structures and across the performance measures. This means the shrinkage model always brings to investors extra return compared with the market in all situations we consider. For example, after covering the high transaction cost of 1%, Carhart's alpha for portfolios using this shrinkage model is 1.62 in Brazil, 1.70 in Russia, 1.07 in India and 1.11 in China and its t-statistic is 2.71 in Brazil, 2.04 in Russia, 2.79 in India and 2.37 in China correspondingly.

Semiparametric skills sometimes can improve their parametric precedent models' performance: when we adopt Carhart's methodology for the performance measure in Russia, although it could if cost-free, the FDP(1,1,1,1) model could not show performance excess to the market after covering transaction cost fixed at 0.5%; but the semiparametric method could add value to investors by changing Carhart's alpha to be significantly positive. For other situations of no impressive improvement by semiparametric skills, a reasonable direction for future research is to enlarge the searching range for optimal bandwidth coefficient, whose current version may be too narrow to be true. We leave this for future research.

For model averaging, in all countries 'thick' and equal weighting could outrun the benchmark if we do not consider transaction cost; but fail to do that in most situations with 1% transaction cost. Another interesting finding is about within-group relative ranking of averaging methods: if the BMA method works then two other averaging methods also show superior results. Also, within the 'thick' group, the quantile threshold of best 25% and best 50% seem better than that of best 15%. This is intuitionally consistent with Granger's (1989) suggestion of including more models for averaging.

4. Conclusion

In this paper, we address the problem of exploiting excess returns via multivariate conditional volatility and correlation modelling in four emerging stock markets: Brazil, Russia, India and China. In application, the minimum variance portfolios are constructed on the basis of both academic and practitioner's ad hoc methods. Zero, low and high costs are devised as 0, 0.5 and 1, respectively of a percentage on trading. From the point of view of assessing model predictability, four performance measures (portfolio's averaged monthly return, Sharpe ratio, intercept variable in Carhart's 4-factor performance regression and its t-statistic) are employed and discussed in detail. In general, our findings confirm that even after covering high transaction costs some methods still outrun the market although the higher the transaction cost, the stronger the wearing-away effect of cost on portfolio performance. Furthermore, a 'super-star' model, which beats the market across the countries, cost structures and performance measures, is found. Given the limited improvement of semiparametric skills in some cases, it is worth paying more attention to optimal bandwidth searching. Another conclusion emerging from our study is that within averaging methods, 'thick' and equal weighting work better than BMA while the quantile threshold in 'thick' is essential.

Notes on contributors

Aman Ullah is a professor in economics at Economics Department, University of California at Riverside. His research interests are econometric theory, applied econometrics and statistics.

Xiangdong Long is a research fellow at the Centre for Financial Analysis and Policy, Judge Business School, University of Cambridge. His research interests are econometrics, time series, empirical finance and financial econometrics.

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