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Dynamic linkages between developed and BRICS stock markets: Portfolio risk analysis

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ABSTRACT

This study examines the dynamic correlations and portfolio diversification between the major developed and BRICS stock markets. The results reveal a significant variability in the time-varying conditional correlations between these markets during upturn and downturn periods. We underline the importance of overweighting the optimal portfolios with stocks from the developed countries over those from the BRICS. Finally, we demonstrate the usefulness of using developed market stocks in the BRICS stock portfolio risk management.

1. Introduction

Financial markets have been characterized by high volatility particularly during periods of structural breaks like the recent global financial crisis (GFC) and the Eurozone sovereign debt crisis (ESDC). These markets also exhibit asymmetric behavior in response to positive and negative shocks during bull and bearish markets, which leads to portfolio re-balancing as a result of changing correlations (Mensi et al., 2014; Zhang et al., 2013). Thus, understanding the volatility behavior of stock markets during major events and crises, particularly the time-varying conditional correlations between the most important emerging markets such as the BRICS (Brazil, Russia, India, China, and South Africa) and the major developed stock markets (United States, Japan, Germany, United Kingdom and France) a key challenge for international investors and policy makers in order to be able to make sound decisions (Hammoudeh et al., 2016; Mensi et al., 2016; Yarovay and Lau, 2016).

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The recent GFC and ESDC provide an opportunity to observe sharp changes in market contagion and volatility transmissions between developed (U.S., European and Japanese) and BRICS markets.[1] In particular, Dimitriou et al. (2013) find evidence of a decoupling effect for most BRICS markets during the early stages of the crises, with linkages re-emerging (recoupling) after the Lehman Brothers bankruptcy, indicating a shift in investors' risk appetite. Mensi et al. (2016) find the four BRIC (Brazilian, Indian, Chinese and South African) markets to be strongly affected by the GFC, supporting the recoupling or increased linkage hypothesis between developed and emerging markets. In contrast, the decoupling hypothesis is supported only for the Russian stock market.

This study considers the issue of spillover effects between the five emerging BRICS and the five major developed stock markets, while accommodating the effects of the properties of long memory, volatility power and volatility asymmetry, which have not been given a proper consideration in previous studies despite their importance in expressing the behavior of financial markets. Thus, the main aim of this study is to examine the dynamic spillovers between those five fast-growing BRICS economies and the five major developed stock markets. We then provide the financial implications of the dynamic linkages among these markets for portfolio risk management through an analysis of mutual time-varying hedging strategies suitable for optimal portfolios and designing financial strategies for risk reduction.

This study makes at least three major contributions to the existing literature. First, it uses the bivariate Dynamic Conditional Correlation Fractionally Integrated Asymmetric Power ARCH (DCC-FIAPARCH) model to examine the dynamic spillover effects between the BRICS and developed stock markets, which is of great significance for having portfolio risk assessment and benefiting from portfolio diversification. The use of the DCC-FIAPARCH model captures prominent financial series properties and is supported by statistical criteria. Second, we quantify the optimal weights and the dynamic hedge ratios of the developed-BRICS stock portfolios. Finally, we measure and analyze risk/ downside risk reductions as a result of portfolio risk management.

The remainder of this study is organized as follows. Section 2 discusses the methodology. Section 3 describes the data and conducts some preliminary analyses. Section 4 discusses the empirical results and draws implications for risk management. Section 5 concludes.

2. Methodology

The AR(1) model in which the dynamics of current stock returns are explained by their lagged returns is defined as follows:

$$r_t = \mu + \xi r_{t-1} + \varepsilon_t,\ t \in N \quad \text{with } \varepsilon_t = z_t\sqrt{h_t} \tag{1}$$

where $|\mu| \in [0, \infty)$, $|\xi| < 1$ and the innovations $\{z_t\}$ follow the Student-t distribution ($z_t \sim ST(0, 1, \nu)$).[2] The conditional variance h_t is positive with probability one and is a measurable function of the variance-covariance matrix $\sum_{t-1}$.

The FIAPARCH (p, d, q) model of Tse (1998) formally expressed as follows:

$$h_t^{\delta/2} = \omega[1-\beta(L)]^{-1} + \left[1-[1-\beta(L)]^{-1}\phi(L)(1-L)^d\right](|\varepsilon_t| - \lambda\varepsilon_t)^\delta, \tag{2}$$

where ω, β, ϕ, and d are the parameters to be estimated. The parameter d where $0 \le d \le 1$ measures the long-range memory in the conditional volatility, L denotes the lag operator, δ is the power term of returns for the predictable structure in the volatility persistence, and $\lambda > 0$ represents the asymmetry parameter indicating that negative shocks give rise to higher volatility than positive shocks of equal size.

In order to obtain the dynamic conditional correlations between the analysed variables, we review the DCC model of Engle (2002). Assume that $E_{t-1}[\varepsilon_{i,\,t}]=0$ and $E_{t-1}[\varepsilon_{i,\,t}\varepsilon'_{i,\,t}]=H_t$, where $E_t[\bullet]$ is the conditional expectation on using the information set available at time t. The conditional variance-covariance matrix, H_t, can be written as:

$$H_t = D_t R_t D_t, \tag{3}$$

where $D_t = diag(h_{11,t}^{1/2}\cdots\cdots h_{NN,t}^{1/2})$ is the $N \times N$ diagonal matrix of conditional standard deviations of the residuals, which are obtained from taking the square root of the conditional variance modelled by an univariate AR(1)-FIAPARCH(1,d,1) model. Moreover, R_t is a matrix of time-varying conditional correlations, which is given by:

$$R_t = \left[\rho_{ij,t}\right] = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2} \tag{4}$$

The unconditional variance-covariance matrix ($\bar{Q}$) depends on the standardized residuals ($u_{i,t} = \varepsilon_{i,t}/\sqrt{h_{ii,t}}$), and its own lagged value according to the below Eq. (5) as:

$$Q_t = (1-\kappa_1-\kappa_2)\bar{Q} + \kappa_1 u_{t-1}u'_{t-1} + \kappa_2 Q_{t-1} \text{ with } \kappa_1, \kappa_2 > 0 \text{ and } \kappa_1+\kappa_2 < 1, \tag{5}$$

[1] Numerous studies have examined the volatility transmission behavior for emerging markets, particularly the BRICS markets, under the recent financial crises (Ahmad et al., 2013; Zhang et al., 2013; Mensi et al., 2014; Bhuyan et al., 2016).

[2] The Student-t distribution is estimated with the parameter (ν), which represents the number of degrees of freedom (df) and measures the degree of leptokurtosis displayed by the density (Fiorentini et al., 2003).