Modeling dependence structures among international stock markets: Evidence from hierarchical Archimedean copulas

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1. Introduction

The past few decades have witnessed a steady rise in studies of the economies and finance in traditional emerging markets. However, frontier markets, new emerging markets with characteristics less developed than those of traditional emerging markets, are now attracting the attention of global investors. Although frontier markets are smaller and less accessible than traditional emerging and developed stock markets, they are still investable because of their high value potential. Frontier markets are not only growing in importance, as evidenced by the recent listings of new mutual funds and exchange-traded funds, but also rapidly developing in economic and financial terms. Therefore, understanding the dependence structure among international equity markets, including developed, traditional emerging, and frontier markets, is of increasing significance to global investors for managing asset allocation and risk and planning diversification strategies.

Most research on international equity returns focuses on the relationships between developed and emerging markets (see Long et al., 2014; Yang and Hamori, 2013; Zhang et al., 2013) or between emerging and frontier markets (see Baumöhl and Lyócsa, 2014; De Groot et al., 2012; Samaracaoon, 2011). For example, De Groot et al. (2012) stated that value, momentum, and local size returns in frontier markets cannot be explained by global risk factors. Mensi et al. (2014) documented that the global financial crisis influenced the dependence structure between emerging markets and global stock and commodity markets.

However, by comparison, research on the relationships among developed, traditional emerging, and frontier markets is limited. For example, Samaracaoon (2011) found that interdependence is driven more by U.S. shocks, while contagion, by emerging market shocks. In addition, frontier markets also exhibit interdependence and contagion to U.S. shocks. Baumöhl and Lyócsa (2014) estimated an asymmetric dynamic conditional correlation (DCC) between traditional emerging and frontier markets.

Previous studies of co-movement dynamics in international stock markets have been based on generalized autoregressive conditional heteroscedasticity (GARCH) and vector autoregressive (VAR) models. However, the main drawback of these approaches is their restricted linear correlation coefficients, which cannot correctly capture the dependence structure among assets. Sklar’s (1959) theorem introduced copula functions, which allow us to combine univariate distributions to obtain a joint distribution with a particular dependence structure. However, to better quantify market dependencies
risks, asset volatility and dependence structure should be considered. The copula-GARCH (C-GARCH) model is a multidimensional GARCH process that models the dependence structure by using a copula function. The application of the C-GARCH model has recently attracted increased academic attention (see Jondeau and Rockinger, 2006; Yang and Hamori, 2013). For instance, Yang and Hamori (2013) evidenced that emerging markets are sensitive to external negative news (downside risk) from developed markets and that the process of dependence changes during crisis periods.

This study advocates the use of the hierarchical Archimedean copula (HAC)-based multivariate GARCH (HAC-MGARCH) model to describe the dynamic dependence among developed, emerging, and frontier markets. The shortcoming of traditional copulas is that they cannot easily model the dependence structure of three or more markets (developed, emerging, and frontier markets). To do so, the developed market here is treated differently according to its location, considering information transmission.

The remainder of this paper is organized as follows. Section 2 discusses the methodology used in this paper. Section 3 describes the data and statistical issues. Section 4 provides the empirical results. Section 5 concludes.

2. Methodology

This study estimates the marginal distributions of data series by using the \( (AR(k)) \)-GARCH\((p, q) \) model. By using the estimated marginal distributions, HAC (Okhrin et al., 2013) is employed to investigate the dependence structure among international stock markets. In addition, the marginal joint distribution from HAC is used to model the conditional correlations among international stock markets.

2.1. Marginal specifications

Dependences among international stock markets can be examined by combining copula functions with a GARCH-type model (Bollerslev, 1987; Engle, 1982) of conditional heteroscedasticity. This model not only successfully describes the characteristics of volatility clustering in stock returns, but also eliminates serial dependence from the component time series. The \( (AR(k)) \)-GARCH\((p, q) \) specification is expressed as follows:

\[
\begin{align*}
\epsilon_t &= \epsilon_{t-1} + \sum_{j=1}^{p} \alpha_j \epsilon_{t-j} + \sum_{j=1}^{q} \beta_j \mu_{t-j} + \mu_t \quad (1) \\
\mu_t &= \omega_t + \sum_{j=1}^{k} \beta_j \epsilon_{t-j} + \sum_{j=1}^{p} \alpha_j \epsilon_{t-j} \quad (2)
\end{align*}
\]

where \( \epsilon_{t-1} \) is the conditional information operator based on the information at time \( t-1 \). Eq. (1), the \( AR(k) \) model, indicates that the current movement of a variable \( x_t \) can be explained by its own past movement \( \{x_{t-1}, x_{t-2}, \ldots\} \). In this paper, the variable \( r_t \) is represented by the \( i \)-th asset return at time \( t \). Eq. (2) denotes that each volatility has a GARCH\((p,q) \) process.

Since the error term \( \epsilon_t \) expressed are skewed and heavy tailed, the density function of \( \epsilon_t \) is assumed to follow a Student’s \( t \) distribution\(^4\):

\[
f(t) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\nu\pi}\Gamma\left(\frac{1}{2}\right)} \left(1 + \frac{t^2}{\nu}\right)^{-\frac{\nu+1}{2}},
\]

where \( \nu \) is the number of degrees of freedom and \( \Gamma \) is the gamma function. The Ljung–Box Q test is applied to examine the residuals of the AR term. According to Schwarz’s Bayesian information criteria and residual diagnostics, the values of \( k, p, \) and \( q \) are such that \( k = 1, 2, \ldots, 5; p = 1, 2; \) and \( q = 1, 2 \).

2.2. Copula functions

Copulas are increasingly used to model multivariate distributions with continuous margins in various research fields, particularly finance (Aloui et al., 2013; Chollete et al., 2011; McNeil et al., 2005; Zolotko and Okhrin, 2014). The recent surge in the popularity of this model in finance studies can be attributed to Sklar (1959), which remains the cornerstone of the theory of copulas. Following Sklar’s (1959) studies, we assume \( X = (X_1, \ldots, X_d) \) is a random vector with continuous marginal cumulative distribution functions \( F_1, \ldots, F_d \) and joint distribution \( H \). Sklar (1959) showed that the joint distribution \( H \) of \( X \) can be represented as

\[
H(X) = C(F_1(x_1), \ldots, F_d(x_d))
\]

in terms of a unique function \( C : [0,1]^d \rightarrow [0,1] \), which is called a copula. Copulas can conveniently construct a multivariate joint distribution by first specifying the marginal univariate distributions and then investigating the dependence structure between the variables according to different copula functions. In addition, tail dependence can be well described by copulas. Two measurements are generally applied to evaluate tail dependence, namely the upper and lower tail dependence coefficients, which function well regardless of whether the markets are crashing or booming.

By assuming that \( X = (X_1, \ldots, X_d) \) and \( Y = (Y_1, \ldots, Y_d) \) are random variables with marginal distribution functions \( F_i \) and \( G_j \), the coefficient of lower tail dependence \( \lambda_L \) can be computed as follows:

\[
\lambda_L = \lim_{t \rightarrow -\infty} P_{(X,Y)} \left[ Y \leq G^{-1}(t) \mid X \leq F^{-1}(t) \right].
\]

which measures the probability of observing a lower \( Y \) if the condition of \( X \) itself is lower. On the contrary, the coefficient of upper tail dependence \( \lambda_U \) can be estimated by

\[
\lambda_U = \lim_{t \rightarrow \infty} P_{(X,Y)} \left[ Y > G^{-1}(t) \mid X > F^{-1}(t) \right].
\]

When the value of lower tail dependence is the same as that of upper tail dependence, there is “symmetric tail dependence” between the two variables; in other cases, dependence is asymmetric. This approach is, thus, an efficient way in which to order copulas. Moreover, if the \( \lambda_L \) of \( C_2 \) is greater than the \( \lambda_U \) of \( C_1 \), copula \( C_2 \) is more concordant than copula \( C_1 \).

This study considers two types of Archimedean copulas: Gumbel and Clayton. In practice, the class of Archimedean copulas has proven to be convenient to model a wide variety of dependence structures because

\(^4\) The \( t \) distribution is selected on the basis of the Jarque–Bera test results.

\(^5\) The concordant pair indicates the elements of one pair are greater than, equal to, or less than the corresponding elements of the other pair.
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