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BLACK SWAN EVENTS AND SAFE HAVENS: THE ROLE OF GOLD IN GLOBALLY INTEGRATED EMERGING MARKETS⬥

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ABSTRACT

There is evidence to suggest that gold acts as both a hedge and a safe haven for equity markets over recent years, and particularly during crises periods. Our work extends the recent literature on hedging and diversification roles of gold by analyzing its interaction with the stock markets of the leading emerging economies, the BRICS. Whilst they generally exhibit a high growth rate, these economies still experience a pronounced vulnerability to external shocks, particularly to commodity price fluctuations. Using a multi-scale wavelet approach and a GARCH-based copula methodology, we mainly show evidence of: *i*) the time-scale co-evolvement patterns between BRICS stock markets and gold market, with some profound regions of concentrated extreme variations; and *ii*) a strong time-varying asymmetric dependence structure between those markets. These findings are essential for risk diversification and portfolio hedging strategies amongst the investigated markets.

Keywords: Equity markets; Copulas; Gold; Time-scale analysis.
JEL Codes: G1; C14; C32; C51

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1. INTRODUCTION

Portfolio's risk diversification is one of the primary concerns for investors and portfolio managers. The modern portfolio theory suggests that investors can reduce the overall risk of their portfolios by allocating funds to assets that are negatively correlated or less than perfectly positively correlated. Putting it differently, the holding of a diversified portfolio of assets allows investors to improve the portfolio's risk-adjusted return. The quest for diversification benefits has particularly been intensified over the last fifteen years due to the advent of multiple "black swan" events such as the internet bubble burst, the 2007 subprime crisis, the 2008–2009 global financial crisis and the European public debt crisis since late 2009.[1] These severe and unpredictable crises and financial turbulences have deeply depressed prices and increased instability in global stock markets. With the increasing trend of financialization of commodity markets since 2004 (Tang and Xiong, 2012; Cheng and Xiong, 2014), investor community has placed greater attention on commodity futures because they have low correlations with stocks and are driven by risk factors that are different from those that affect stock returns (Gorton and Rouwenhorst, 2006; Dwyer et al., 2011; Bekiros et al., 2017). For instance, Bekiros et al. (2017) find, from time-varying network topologies and entropy relationships, that commodity futures markets are heterogeneous, only have strong intra-category connections, and are still decoupled from equity markets. The weak equity-commodity link is thus a desirable feature for portfolio diversification, which has been documented in the past literature on commodity markets' diversifying potential (Arouri et al., 2011; Daskalaki and Skiadopoulos, 2011).

Along with the existing literature on portfolio allocation and diversification, this paper focuses on the role of a particular commodity, gold, as a hedge, a diversifier, and a safe haven asset for stocks issued by five leading emerging stock markets of the BRICS countries (Brazil, Russia, India, China, and South Africa). Our main motivation arises from the fact that, besides its role of inflation hedging, gold still acts as both a hedge and a safe haven for stocks particularly during

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[1] Since Taleb (2010), the black swan theory is commonly used to designate the impossibility of anything like a black swan. We used this expression as a metaphor to describe crises and financial turbulences that happened as a surprise and have harmful and large-scale effects.

crises periods, albeit not identically for all international markets (Baur and Lucey, 2010; Baur and McDermott, 2010; and references therein). In the aftermath of the global financial crisis 2008–2009, gold has even become more attractive given its low perceived risk in an environment of high systematic risk, increased financial uncertainty, continued low demand, and deflationary pressures. The volume of gold traded in 2014 as reported by London Bullion Market Association amounted approximately to 157,000 tones with a value of $5.9 trillion. Among the BRICS countries, only China and India already account for around 40% of the total world gold bar and coin demand (World Gold Council, 2016)[2], while South Africa is the first-largest gold exporter in Africa and China, India, and Russia are among the top 10 countries with the largest gold reserves. At the same time, the role of gold as an investment asset for portfolios of stocks in the BRICS markets has not been explored, while these markets are commodity-dependent and exposed to global shocks due to their increasing integration and co-movement with the rest of the world in the long run (Lehkonen and Heimonen, 2014).[3]

The importance of the BRICS economies in the global growth, their heterogeneity in economic structures and the recent trends in their development suggest that gold may play a different role for each market under consideration. According to the IMF estimates (IMF, 2015), the share of the BRICS countries in global GDP (PPP basis) is expected to be around 33% by 2020 and exceeds that of the G7 by 2017. Negative shocks affecting the BRICS economic and financial systems could thus seriously harm the global growth and financial stability. BRICS are anticipated to exhibit exceptionally high economic growth rates over the next 50 years. Note also that in March 2013, BRICS countries signed an agreement for the creation of New Development Bank (NDB) based in Shanghai, which came into force in July 2015. The NDB aims to "*mobilize resources for infrastructure and sustainable development projects in BRICS and other emerging market economies and developing countries to complement the existing efforts of multilateral and regional fi-*

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[2] http://www.gold.org/download/file/5087/GDT_Q2_2016_Investment.pdf
[3] Lehkonen and Heimonen (2014) further stress that investors can obtain portfolio diversification benefits from investing in the BRIC markets. However, the BRIC countries cannot be treated as a homogeneous group of emerging economies in terms of stock market co-movement.

nancial institutions for global growth and development". For this purpose, it will be endowed with an enormous currency exchange reserve of US$100 billion backed by gold.

A number of existing studies have shown evidence of the hedging, diversifying and safe haven potential for stocks and bonds (e.g., Baur and McDermott, 2010; Baur and Lucey, 2010; Beckmann et al., 2015; Gürgün and Ünalmış, 2014; Bredin et al., 2015). For instance, Baur and McDermott (2010) investigate the role of gold in the global financial system with a focus on a sample of major developed and emerging markets (BRIC) and reported gold's safe-haven status with respect to stock market movements over the period 1979–2009, except for Australia, Canada and Japan. Baur and Lucey (2010) use daily data for the period 1995–2005 to estimate constant and time-varying relationships between the U.S., U.K. and German stock and bond returns and gold returns. These authors find that gold is on average a fair hedge against stocks and a safe haven in extreme stock market conditions. Beckmann et al. (2015) extend further the literature by using a smooth transition regression (STR) model that allows to test the hedging and safe haven hypotheses of gold conditionally on the transition between two extreme regimes (normal times versus crisis times). They reach similar conclusions as in Baur and Lucey (2010) for a larger sample of 18 individual markets and five regional indices over a longer period from 1970 to 2012. In related studies, Hammoudeh et al. (2011) document the importance of other precious metals besides gold in risk management, while Conover et al. (2009) suggest that investors could considerably improve portfolio performance by adding the equities of precious metals firms to portfolios of the US stocks. Riley (2010) also shows that precious metals have, in general, notable advantages like high expected returns and negative correlations vis-à-vis other asset classes, and this is particularly true in the presence of instable macroeconomic conditions and economic policy uncertainty. On the other hand, some studies show that gold's hedging and diversification potential can be reduced due to increased co-movement and volatility transmission following financialization of commodity markets (Gromb and Vayanos, 2010; Silvennoinen and Thorp, 2010; Daskalaki and Skiadopoulos, 2011; Adams and Glück, 2015).

There is also evidence on the specific characteristics of gold returns as well as on the role of gold as a hedge and safe haven for other asset classes such as exchange rates and oil price fluctuations (e.g., Joy, 2011; Ciner et al., 2013; Baur, 2013; Reboredo, 2013 a,b). Baur (2013) analyzes the dynamics of monthly gold returns and finds evidence of seasonality (autumn effect) since September and November were the only months with positive and statistically significant gold price changes over the period 1980–2010. Using a model of dynamic conditional correlation, Joy (2011) investigates whether gold could act as a hedge against the US dollar and finds that it has behaved quite consistently during the past 23 years. Reboredo (2013a) uses a copula approach to assess the role of gold as a safe haven against the US dollar and shows that the significant and positive unconditional dependence between gold and dollar depreciation is consistent with the view that gold can act as a hedge against the fluctuations of the US dollar value. It is also demonstrated that there exists a symmetric tail dependence between gold and US dollar exchange rates, indicating that gold could be considered effective even against extreme upside or downward US dollar movements.

Overall, our research contributes to the existing literature by investigating the hedging, diversifying, and safe haven roles of gold for stock portfolios in the BRICS stock markets. Following Baur and Lucey (2010), we define gold as a hedge if it is uncorrelated or negatively correlated with the stock portfolio, as a diversifier if it is positively but not perfectly correlated with the stock portfolio, and finally as a safe haven if it is a hedge for the stock portfolio in times of crises/extreme situations. We develop a combined framework of frequency-domain causality, continuous wavelet transforms and time-varying copulas to achieve our objective. More precisely, this framework allows us to improve the common understanding of causal interactions between gold and BRICS stock markets as well as the analysis of their "phase-cycle" co-movement (i.e., in-phase/out-of-phase and lead-lag patterns), at both the aggregate and scale-dependent levels, to the extent that economic agents may have different term objectives. It also enables an enhanced investigation of the gold-stock conditional dependence, through copulas, which allows as-

sessing the hedging and diversifying hypotheses of gold in both normal and extreme market conditions.

Using 3-month gold futures prices that incorporate investors' expectations regarding gold investments and MSCI stock market indices, our results mainly show evidence of heterogeneity of causal interactions between gold and BRICS stock markets with causality from gold to stocks being more important in short to medium horizons. They also indicate an increase in gold-stock co-movement in the long run and a leading effect of gold market over the BRICS stock markets during the recent global financial crisis. Finally, we document a time-varying conditional dependence between gold and stocks, which is larger during bad times than during good times.

The rest of the paper is organized as follows. Section 2 describes the data and their stochastic properties. Section 3 presents the methodology based on time-frequency causality tests, continuous wavelet transforms, and copula approach. Section 4 reports and discusses the empirical results. Section 5 provides concluding remarks and implications of the findings.

2. DATA AND STOCHASTIC PROPERTIES

This paper uses the equity market indices of Morgan Stanley Capital International to represent the portfolio of stocks in the BRICS emerging market countries and the 3-month futures prices for gold from New York Mercantile Exchange (NYMEX). Futures prices of gold are employed instead of spot prices because they implicitly incorporate investors' expectations about the future dynamics of gold prices which is an important indicator for portfolio design and allocation. It is worth noting that the continuous gold futures prices in our study are perpetual series of futures prices derived from individual futures contracts and rolled over on the 1st business day of the new notional contract month. Daily data are collected for the period from 01 January 2000 to 31 July 2014. To the extent that this study period covers the full episode of the global financial crisis of 2007–2009 where both stock and gold prices exhibited long swings and unstable fluctuations particularly due to the credit crunch, the loss of confidence and the high degree of financial and

economic uncertainty, we are able to investigate the role of the gold (and gold futures contracts) vis-à-vis the BRICS stock markets during both normal and crisis periods.

Our empirical analysis relies on the logarithmic returns which are computed by taking the difference in the natural logarithm of two successive daily index prices. Table 1 reports the summary descriptive statistics of stock and gold market returns. Daily average returns are positive for all stock markets under consideration, with India exhibiting the highest return (0.030%) and Russia the lowest return (0.023%). Gold futures provided a higher return (0.039%) than the BRICS stock market returns. The unconditional volatility, as measured by the standard deviation, ranges from 0.018 (India and South Africa) to 0.026 (Russia) for emerging stock markets, while it is 0.012 for gold futures. The risk-adjusted return ratio indicates that high risk is not always compensated by high return in emerging stock markets. Given its highest risk-adjusted return ratio of 3.25%, gold futures asset is an interesting investment offering the highest return for the lowest risk.

[Insert Table 1 about here]

Skewness coefficients are negative and kurtosis coefficients are greater than three for all markets, suggesting that return distributions are asymmetrical and have fatter tails than the corresponding normal distributions. This result is confirmed by the Jarque–Bera test that clearly rejects the null hypothesis of normality. In addition, the results of the Ljung–Box test applied to both return series and squared return series with 12 lags indicates that returns and squared returns are serially correlated as the null hypothesis of independence is rejected at the 1% threshold level. The Engle's (1982) ARCH test with 12 lags rejects the null hypothesis of homoscedasticity for all return series, thus suggesting the use of GARCH-type models for capturing empirical stylized facts of returns such as volatility clustering and time-variations. Moreover, the stationarity and unit root tests for both price and return series indicate that prices are not stationary but returns are stationary at conventional significance levels[4].

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[4] The optimum lag length is selected based on the Schwarz Information Criterion (SIC). For the sake of brevity, we do not present the results here, but they are available from the authors upon request.

Regarding the correlations between gold futures and stock market returns, they are low and range from 0.09 (Gold-China) to 0.28 (Gold-South Africa). The highest correlation with gold futures observed for South Africa seems to be directly linked to this country's resource-rich economy. These low correlations typically suggest that investors can obtain diversification benefits from adding gold futures to their portfolios of stocks in the BRICS countries.

[Insert Figure 1 and Figure 2 about here]

To give an idea of how BRICS stock markets and gold futures markets evolve over time, we depict, in Figures 1 and 2, the dynamics of the log price and log return series. While stock prices in the BRICS markets experienced two sharp decreases following the burst of the internet bubbles in 2001 and the Global Financial Crisis in 2008–2009, gold futures prices exhibited a continual increasing trend since the early 2000s, with a decreasing tendency from the second quarter 2013. This recent decline in gold prices could potentially be explained by, among others, the recovery of stock markets around the world, the strengthened US dollar, the expected rise in the US interest rate, which reduce the demand for gold as a safe haven asset. It is also worth noting that after the Subprime crisis and the Lehman Brothers collapse, China and Russia incorporated gold as an integral part of their newly designed monetary system in an attempt to counterbalance the adverse effects of the financial turmoil as well as to compete in terms of capital inflows. The potential of hedging and diversification benefits from investing in gold has thus become an issue of utmost importance for investors having exposure to the BRICS stock markets.

3. METHODOLOGY

As stated earlier in the introduction, we use continuous wavelet transforms and copula models to examine the role of gold as a hedge, a diversifier, and a safe haven for stock portfolios in the BRICS countries. This framework is advantageous in that it offers a flexible way to precisely gauge, through wavelets, the potential nonlinear co-movement between gold and stock markets

and its strength over time and different scales (periodicities)[5]. A high degree of time-scale co-movement thus implies a reduced diversifying potential of gold, while a negative time-scale co-movement suggests a hedging potential of gold. On the other hand, copulas allow for capturing the dependence structure (i.e., symmetric versus asymmetric dependence, and left-tail versus right-tail dependence) between considered markets. The sign and amplitude of copula's dependence parameter decide the role that gold plays vis-à-vis the stock portfolios in the BRICS markets. It is worth noting that a frequency-domain test is also carried out, as a preliminary analysis before exploring the wavelet-based co-movement and copula dependence, to highlight the possible causal linkages between gold and BRICS stock markets.

3.1 Frequency-domain causality analysis

The frequency-based connectedness of random variables provides insightful information about the nature of their directional causality over various time scales (periodicities). To the extent that the standard causality test is unable to detect the time-scale directional causality (Lemmens et al., 2008), we use the Breitung and Candelon (2006)'s frequency-domain test, which is fundamentally based on the works of Granger (1969) and Geweke (1982), to study whether time-scale causal interactions between gold and BRICS stock markets do exist. Accordingly, the link between stock returns (E_t) and gold returns (G_t) under a stationary Vector Autoregressive (VAR) model can be described as

$$\begin{cases} E_t = a_1 E_{t-1} + \cdots + a_p E_{t-p} + \beta_1 G_{t-1} + \cdots + \beta_p G_{t-p} + \varepsilon_t \\ G_t = b_1 G_{t-1} + \cdots + b_q G_{t-q} + \alpha_1 E_{t-1} + \cdots + \alpha_q G_{t-q} + \eta_t \end{cases} \tag{1}$$

The null hypothesis of the frequency domain causality test that gold returns do not cause stock returns in the frequency interval $\vartheta \in (0, \pi)$ is examined by computing the F-statistics which is approximately distributed as $F(2, T - 2p)$ under the null (see, Breitung and Candelon, 2006 for more technical details). At the empirical level, we are interested in testing the short-, medium- and long-term directional causality. The presence of causality between stock and gold returns at

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[5] Heterogeneous economic agents, black swans, crises, and structural changes in business cycle are among the main factors that cause inter-variable nonlinear links.

different frequencies implies that the specific frequency components of one variable can be predicted by those of the other variable.

3.2 Wavelet analysis of time-scale co-movement

While it provides directional causality at some pre-specified frequency ranges, the Breitung and Candelon (2006) test is unable to reveal possible nonlinear interrelationships between gold and stock returns, which can be efficiently captured by a multiscale wavelet method (Bekiros and Marcellino, 2013). Additionally, wavelets are not restricted to a pre-specified frequency range imposed by the raw data frequency. Earlier applications of wavelets in economics and finance can be found in, among others, Ramsey et al. (1995) for detecting self-similarity in US stock prices and Ramsey and Lampart (1998a,b) for investigating the relationship and causality between money, income and expenditure. Some recent studies have combined wavelets with causality tests (e.g., Gençay *et al.,* 2002; Bekiros et al., 2016).

Since our objective is to uncover the underlying stochastic processes that drive the dynamics of gold and stock returns, their changing cyclical behavior, and their time-scale co-movement, we make use of continuous wavelet transforms (CWT), instead of discrete wavelet transforms (DWT) which are more suitable for multiscale decomposition of the initial signals (Aguiar-Conraria and Soares, 2014). More specifically, we rely on continuous wavelet's power spectrum (i.e., local variance of a single variable) and cross-wavelet coherence (i.e., the local covariance of two variables) analysis.

Let S_t represent the stock market return and G_t the gold futures returns with wavelet power spectra, $W_t^S(r)$ and $W_t^G(r)$, respectively. The cross-wavelet power spectrum is defined as $W_t^{SG}(r) = W_t^S(r) * W_t^G(r)$, while their coherence measure which assesses the time-scale co-movement between gold and stock returns takes the following form (Torrence and Webster, 1999):

$$R_t^2(r) = \frac{\left|Q\left(r^{-1}W_t^{SG}(r)\right)\right|^2}{Q\left|\left(r^{-1}\left|W_t^S(r)\right|^2\right)\right|.Q\left|\left(r^{-1}\left|W_t^G(r)\right|^2\right)\right|} \tag{2}$$

where Q refers to a smoothing operator (Rua and Nunes, 2009). The numerator is the absolute squared value of the smoothed cross-wavelet spectrum, while the denominator is the product of the smoothed wavelet power spectra (Torrence and Webster, 1999; Rua and Nunes, 2009). The wavelet squared coherence $R_t^2(r)$ is bounded between 0 and unity. Monte Carlo simulation method is used to generate the accurate statistical significance of the coherence measure (Torrence and Compo, 1998).

3.3 Copula modeling for conditional dependence structure

Copulas have been widely used to model the dependence structure of financial assets and markets (e.g., Aloui et al., 2011; Christoffersen et al., 2012). They are particularly found to be flexible and effective in modeling and characterizing dependence patterns between variables (tail dependence, symmetric versus asymmetric dependence, and constant versus time-varying dependence). An important advantage of copulas is that the marginal distribution is modeled separately from the dependence structure, which makes easier the selection of accurate marginal models and suitable copula functions.

Let S_t and G_t denote stock and gold futures return series with marginal distribution functions, $F_S(s)$ and $F_G(g)$, respectively and a joint distribution $F_{SG}(s, g)$. Then, according to the Sklar's theorem (Patton, 2006), there exists a copula $C: [0,1]^2 \rightarrow [0,1]$ such that

$$F_{SG}(s, g) = C(F_S(s), F_G(g)) \tag{3}$$

where $C(u, v)$ with $u = F_S(s)$ and $v = F_G(g)$ is a bivariate copula function. The joint density, $f_{SG}(s, g)$, can then be computed as the product between the copula density, $c(u, v)$, and the univariate marginal distributions of the stock and gold futures returns, $f_S(s)$ and $f_G(g)$.

$$f_{SG}(s, g) = c(u, v)f_S(s)f_G(g) \tag{4}$$

where $c(u, v) = \partial^2 C(u, v)/\partial u \partial v$, representing the dependence structure of data. The representation in Eq. (4) implies the following decomposition for the log-likelihood function:

$$L = \log[c(u, v)] + \log[f_S(s)] + \log[f_G(g)] \tag{5}$$

A copula model also offers the possibility to assess the lower (upper) tail dependence which is measured by the probability that two random variables realize extremely small (large) returns together. The tail dependence coefficients are computed as follows:

$$\lambda_L = \lim_{t \to 0} P[G \leq F_G^{-1}(t)|S \leq F_S^{-1}(t)] \tag{6}$$

$$\lambda_U = \lim_{t \to 1} P[G \geq F_G^{-1}(t)|S \geq F_S^{-1}(t)] \tag{7}$$

where λ_L and $\lambda_U(v) \in [0.1]$.

In our empirical setting, we consider various types of symmetric copulas (normal, Student-*t*, Plackett, and Frank), asymmetric copulas (Gumbel, Rotated Gumbel, and Symmetrized Joe–Clayton copula or SJC), and time-varying copulas (normal, Student-*t*, and SJC) to model the dependence structure between stock and gold returns. Depending on the value and sign of copula's dependence parameters, we are able to empirically assess the hedging and diversifying hypotheses of gold in both normal and extreme market conditions where the dependence in the tails happens. A positive and high value of the copula's lower tail dependence parameter would imply that gold does not serve as a safe haven for stocks in the BRICS countries.

For all u, v in $[0,1]$, the bivariate normal and Student-*t* copulas are defined by

$$C^{Normal}(u, v; \rho) = \Phi(\Phi^{-1}(u), \Phi^{-1}(v)) \tag{8}$$

$$C^{Student-t}(u, v; \rho, \vartheta) = T_\vartheta(t_\vartheta^{-1}(u), t_\vartheta^{-1}(v)) \tag{9}$$

where Φ and T_v represents the bivariate standard normal distribution and the bivariate Student-*t* distribution with degree of freedom ϑ, while Φ^{-1} and t_ϑ^{-1} are the inverse of the standard normal and Student-*t* distributions. $\rho \in [-1,1]$ is the linear correlation coefficient. While both the normal and Student-*t* copulas capture the symmetric dependence structure, there is no tail dependence for the normal copula.

The Plackett copula (Plackett, 1965) and the Frank copula (Frank, 1979) are also symmetric and able to capture the full range of dependence for marginal with exposure to tail dependence. They are given in equations (10) and (11).

$$C^{Plackett}(u, v; \theta) = \frac{(1+(\theta-1)(\theta+v)-\sqrt{[1+(\theta-1)(u+v)]^2-4\theta(\theta-1)uv}}{2(\theta-1)}, \theta \in [0, \infty] - 1$$

(10)

$$C^{Frank}(u, v; \lambda) = \frac{-1}{\lambda} \log \left[\frac{(1-e^{-\lambda})-(1-e^{-\lambda u})(1-e^{-\lambda v})}{(1-e^{-\lambda})} \right], \lambda \in [-\infty, \infty] \qquad (11)$$

Regarding the asymmetric copulas, the Gumbel copula (Gumbel, 1960) and its rotated version are given by

$$C^{Gumbel}(u, v; \delta) = exp\left\{-[(-logu)^\delta + (-logv)^\delta]^{1/\delta}\right\} \qquad (12)$$

$$C^{Rotated\_Gumbel}(u, v; \delta) = u + v - 1 + C^{Gumbel}(1 - u, 1 - v; \delta) \qquad (13)$$

where the dependence parameter $\delta \in (1, \infty)$. The Gumbel copula has greater dependence in the upper tails ($\lambda_U = 2 - 2^{\frac{1}{\delta}}$ and $\lambda_L = 0$), while the rotated Gumbel copula has the inverse dependence structure of the Gumbel copula ($\lambda_U = 0$ and $\lambda_L = 2 - 2^{\frac{1}{\delta}}$).

The Symmetrized Joe–Clayton copula SJC (Patton, 2006) allows for capturing asymmetric tail dependence and is specified as

$$C^{SJC}(u, v; \lambda_U^{SJC}, \lambda_L^{SJC}) = 0.5[C^{JC}(u, v; \lambda_U^{JC}, \lambda_L^{JC}) + C^{JC}(1 - u, 1 - v; \lambda_U^{JC}, \lambda_L^{JC}) + u + v - 1] \quad (14)$$

where $C^{JC}(u, v; \lambda_U^{JC}, \lambda_L^{JC}) = 1 - \{1 - [(1 - (1 - u)^\kappa)^{-\gamma} + (1 - v)^\kappa]^{-1/\gamma}\}^{1/\kappa}$ is the Joe-Clayton copula, $\kappa = 1/log_2(2 - \lambda_U^{JC})$, $\gamma = -1/log_2(\lambda_L^{JC})$, $\lambda_U^{JC} \in (0,1)$, and $\lambda_L^{JC} \in (0,1)$. The SJC dependence structure is symmetric if $\lambda_U^{JC} = \lambda_L^{JC}$, otherwise it is asymmetric.

To account for the potential of time-varying dependence between gold and stock returns, we consider several time-varying copulas with both symmetric and asymmetric dependence patterns. Similar to Patton (2006), we let the dependence parameter of the Gaussian and Student-t copulas follow an ARMA(1,p) process as in equation (15) where $\Omega(x) = (1 - e^{-x})(1 - e^{-x})^{-1}(x)$ is a logistic transformation to keep ρ_t within $[-1,1]$. It is worth noting that for the Student-t copula, $\Phi^{-1}(x)$ is substituted by $t_v^{-1}(x)$. Similarly, the dependence parameter of the rotated Gumbel copula, and the extreme dependence parameters of the SJC copula are modeled as in equations (16)–(18).

$$\rho_t = \Omega \left[\Psi_0 + \Psi_0 \rho_{t-1} + \Psi_2 \frac{1}{q} \sum_{j=1}^{q} \Phi^{-1}(u_{t-j}) \cdot \Phi^{-1}(v_{t-j}) \right] \tag{15}$$

$$d_t = \Omega \left[\Psi_0 + \Psi_0 d_{t-1} + \Psi_2 \frac{1}{q} \sum_{j=1}^{q} |u_{t-j} - v_{t-j}| \right] \tag{16}$$

$$\tau_{U,t}^{SJC} = \Omega \left[\Psi_0^U + \Psi_1^U \tau_{U,t-1}^{SJC} + \Psi_2^U \frac{1}{10} \sum_{j=1}^{10} |u_{t-j} - v_{t-j}| \right] \tag{17}$$

$$\tau_{L,t}^{SJC} = \Omega \left[\Psi_0^L + \Psi_1^L \tau_{U,t-1}^{SJC} + \Psi_2^L \frac{1}{10} \sum_{j=1}^{10} |u_{t-j} - v_{t-j}| \right] \tag{18}$$

We apply the two-step approach proposed by Joe (1997) to compute the inferences of the copula density and marginal models. In the first step, we choose the best-suited marginal models among the various competing GARCH-type specifications (GARCH, EGARCH, GJR-GARCH and FIGARCH) for modeling gold and BRICS stock market returns. Our results based on Log-likelihood ratio and SIC criterion select the GJR-GARCH(1,1) specification as the most suitable marginal model for all return series. This model, as described in Eq. (19), particularly allows for capturing heavy tails and asymmetric volatility. The maximum likelihood method is used to estimate its parameters.

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} \tag{19}$$

where ε_t follows a skewed Student-t distribution. $I_{t-1} = 1$ if $\varepsilon_t < 0$ and otherwise $I_{t-1} = 0$. Glosten *et al.* (1993) show that the positivity and stationarity of the volatility process are guaranteed whenever the parameters satisfy the constraints $\omega, \alpha, \beta, \gamma > 0$, and $\frac{\gamma}{2} + \alpha + \beta < 1$.

In the second step, each marginal estimated from the GJR-GARCH model is plugged into the copula likelihood function as defined in Eq. (5) and the latter is maximized with respect to the unknown vector of copula parameters.

4. EMPIRICAL RESULTS

4.1 Causal interactions and time-frequency co-movement

We carry out the Breitung and Candelon (2006) spectral-domain test to uncover both the short- and long-run causality within a wide range of frequencies in the interval $[0, \pi]$. Figure 3 illustrates the bivariate relationships amongst all investigated gold-stock pairs. The frequency on the

horizontal axis ϑ can be interpreted as a cycle or periodicity of T days where $T = 2\pi/\vartheta$. We consider four spectral bands for the causality from gold return to stock return and the other way around: *i*) very short-run horizons corresponding to $\vartheta \in [0,0.5]$, *ii*) short-run horizons with $\vartheta \in [0.5,1.5]$, *iii*) medium-run horizon with $\vartheta \in [1.5,2.5]$, and *iv*) the longest time periods laying in the interval $[2.5, \pi]$. Specifically, short-run and long-run causal interactions between gold and stock returns together with the critical value of the statistical test at the 5% and 10% levels are displayed towards the left and the right of the graph, respectively.

[Insert Figure 3 about here]

The results from the spectral-domain test (Figure 3) reveal the existence of bidirectional causality at different frequency bands for all stock-gold pairs. More precisely, there is evidence of significant causality from the Brazilian stock market to gold over both the short-run and long-run horizons, i.e., (0.00, 1.05) and (2.40, 2.70) frequency bands, as the test statistics largely exceeds the critical values at the 5% and 10% levels. The reverse causality from gold to stock market in Brazil is observed at very short-run (0.00, 0.30), medium-run (1.35, 2.30) and long-run (2.50, 2.95) periodicities. For the Russia-gold pair, the causality runs from stock markets to gold for (0.00, 0.50), (0.60, 1.10), (1.35, 1.52) and (2.25, 2.70) frequency bands, while the reverse causal effect is found for the short- and long-run horizons. For India and China, the causality from stock markets to gold occurs within (0.00, 0.90) and (2.25, 2.96) frequency bands for India, and (0.00, 1.10) and (1.55, 2.40) frequency bands for China. Gold only causes changes in the Indian stock market at the medium-term (1.15, 1.60), but has significant effects on stock market of China at all frequency bands, including the following day intervals (0.00, 0.60), (1.15, 1.75) and (2.40, 2.90). For South Africa, gold is caused by the stock market returns at almost all frequency bands such as (0.00, 0.60), (1.40, 1.60) and (2.35, 2.70), whereas it only has causal effects on stock market re-turns at the short-run and medium-run horizons.

Taken together, the frequency-based causality test indicates that the causality from BRICS stock markets to the gold market is more pronounced than the other way around, particularly at

the short-run and long-run horizons. This finding may imply that short-term shocks in stock markets can be quickly transmitted to the gold market. For example, a stock market crash or downturn could lead to a rise in gold prices to the extent that stock investors allocate more funds to gold to diversify away the stock risk. On the contrary, the causality from gold to equity markets happens more at the short-run and medium-run horizons, which suggests that investment strategies in stock markets can be designed independently from the gold market fluctuations if stock investors pursue a long-run objective. Besides the frequency-dependent effects, the evidence of causal interactions is consistent with the existence of time-varying volatility transmission and dynamic co-movement between gold and stock markets (Arouri et al., 2015 and references therein), which may reduce the ability of gold as a safe haven for stocks during crisis periods.

We now turn to the multiscale wavelet analysis of co-movement, which allows for capturing potential of nonlinear linkages between gold and stock returns while avoiding the shortcomings of Breitung and Candelon test (i.e., linearity of the model parameters, threshold constraint depending on input data frequency, and short length of frequency bands). The use of the continuous wavelet transform (CWT) approach is particularly important in that it enables the possibility to allows us to investigate the scale-dependent and nonlinear (a)synchronization between gold and BRICS stock markets both over time and across frequencies. Indeed, the time-varying linear and nonlinear phase-dependent linkages including the second or higher order effects (which is not possible with the linear correlation coefficient) can be fully captured by the wavelet coherence measure described in Section 3. The changes in the wavelet coherence measure typically reflect the heterogeneity of market participants and their investment horizons in both gold and stock markets. From a practical point of view, short-term investors are interested in interim price fluctuations, while long-term agents tend to adjust their investment decisions based on the long-run price movements.

[Insert Figure 4 about here]

Figure 4 presents the contour graphs of the estimated wavelet coherence for gold returns and each of the BRICS market returns. The thick black contour lines display the 95% confidence intervals estimated from Monte Carlo simulations using phase-randomized surrogate series. The vertical and horizontal axes show the frequency and the study period in days, respectively. The color presentation ranges from blue to red where the blue color indicates a low level of coherence (low co-movement between variables under consideration) and the red color indicates a high level of coherence. In particular, the horizontal axis divides the time period into seven thresholds, i.e., 500, 1000, 1500, 2000, 2500, 3000 to 3500 days, which corresponds to the following dates: 3 December 2001, 3 November 2003, 3 October 2005, 3 September 2007, 3 August 2009, 4 July 2011, and 3 June 2013, respectively. The starting and ending dates are 4 January 2000 and 31 July 2014. The lighter black line delimits the region with high power and the "cone of influence" where edge effects become important (Torrence and Compo, 1998). The direction of the arrows provides the information about the phase lead-lag relationships between gold and stock markets. Arrows pointing to the right signify phase-synchronized series, while those pointing to the left indicate out-of-phase variables. Moreover, arrows pointing to the right-down or left-up indicate that gold leads the BRICS stock markets, whereas the right-up or left-down arrows show evidence that gold is lagged behind stock market movements. The in-phase regions are indicative of a cyclical interaction between markets, while the out-of-phase (or anti-phase) behavior demonstrates an anti-cyclical effect. Note that the contour plots derived by a three-dimensional analysis enable to detect areas of varying co-movement for a pair of return series over time and across frequencies. The areas of stronger interdependence in the time-frequency domain thus imply lower potential of gold as a hedge and a safe haven for stocks, and thus lower benefits from including gold into stock portfolios.

A close look at the coherence measure graphs (Figure 4) shows that Russia-gold, South Africa-gold, and to a lesser extent Brazil-gold market pairs exhibit a very high degree of in-phase co-movement at the long-term frequency band (more or less than 512 days) over the time period

from 2003M11 to 2011M07 given the concentration of the red regions (orange region at the beginning for Brazil) and the right-direction arrows. A particularity is observed for the South Africa-gold pair as it highly co-moves and synchronizes together from 2002 to 2005 within a higher frequency (between 128 and 450 days). The high degree of long-term co-movement between gold and stock markets in Russia and South African can be explained by the high dependence of these economies on natural resources including gold, particularly in the case of South Africa. It seems also to coincide with the rising tendency of gold prices since 2002 and the increased interest of investors for gold as a diversifying asset in the aftermath of successive crises and financial turbulences (e.g., the Russian economic crisis in 2000–2001, the internet bubble burst in 2001, the global financial crisis 2008–2009). At the higher frequencies or shorter periodicities from 0 to 32 days, the co-movement between gold and stock market returns is generally low since the cross-wavelet power spectra has values below 0.5. At medium-run horizons from 32 to 128 days, the contour plots show some evidence of high co-movement located around the subprime crisis in 2007 and the global financial crisis of 2008–2009, and the cross-market linkage is greater for the subprime crisis.

The direction of arrows in the regions of high co-movement indicates that stock markets in India and Brazil display a time-varying lag-lead relationships vis-à-vis gold in the time-frequency space. Over the higher frequencies up to 128 days (short- and medium-run horizons), we indeed find alternative periods of right-down arrows (i.e., gold market leads the stock market) and then of right-up arrows (i.e., the gold market lags behind the movements in the stock market). However, the leading gold market situation is more frequent than the lagging gold market situation. For the low frequencies (or longer periodicities) from 505 to 610 days, the gold leads the changes in the stock markets of the BRICS countries during the period from 2003M11 to 2011M07 for Brazil and Russia, from 2007M09 to 2012M04 for India, from 2005M10 to 2011M07 for China, and from 2002M11 to 2011M11 for South Africa. It is clear that the gold market significantly leads the stock markets throughout the recent global financial crisis (2008–2009).

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In summary, the above analysis points out a reduction of the hedging/diversifying potential of gold for portfolios of stocks in the BRICS countries over the long run (and thus the reduction of diversification benefits) to the extent than the gold-stock market co-movement increases from the high to the low frequencies. Gold's ability as a safe haven is also not observed given the high degree of its synchronization with stock markets during the global financial crisis. The time-varying co-movement across frequencies suggests that stable (static) hedging coefficient and asset allocation between gold and stocks are not appropriate for portfolio designs. It is important to note that the wavelet analysis confirms the results of frequency-domain test in terms of timescale interactions, but it provides more relevant and meaningful information about the gold-stock relationships.

4.2 Analysis of conditional dependence

As stated earlier, we estimate the copula dependence parameters according to a two-step procedure, where the first step consists of estimating the parameters of the univariate marginal models. Table 2 reports the estimation results of the best-suited marginal model, GJR-GARCH(1,1), for gold and each of the BRICS stock markets. The AR(1) parameter of the mean equations is significant in all cases except for China, suggesting the lack of one-step ahead predictability of stock returns in China. The estimated parameters of the GJR-GARCH(1,1) process are also highly significant. In particular, the conditional volatility is quite persistent since all parameters associated with the lagged conditional variance values of the BRICS and gold market returns (β), ranging from 0.852 (India) to 0.924 (China), are significant at the 1% threshold level. The impact of unexpected shocks (α) is also significant for all markets, except for Brazil.

As to the asymmetry parameters (γ), they are positive and highly significant at the 1% threshold level in all cases, which suggests that the conditional volatility reacts more strongly to bad news than to good news. In addition, the estimated tail parameters (Student-df) are strongly significant with values exceeding two. This finding confirms the relevance and usefulness of the Student-*t* distribution for fitting both gold and stock returns. Even though the departure from

normality still exists, the results of the diagnostic tests show that the GJR-GARCH model with Student-*t* errors is appropriate for modeling the dynamics of stock and gold returns. For this purpose, it is important to note that the ARCH effects completely disappear in residual series and the stability condition for volatility model parameters is satisfied.

[Insert Table 2 about here]

Table 3 presents the results of the conditional dependence structure for pairs of gold and stock markets. Panel A shows the estimates of the dependence parameters for the static copula models together with the log-likelihood (log-lik) and AIC values. Out of four symmetric copulas (Normal, Student-*t*, Frank and Plackett) and five asymmetric copulas (Clayton, Rotated Clayton, Gumbel, Rotated Gumbel, and SJC), both criteria select the Student-*t* copula as the best-suited copula for modeling the dependence patterns between gold and BRICS stock markets. Indeed, the Student-*t* copula has the highest log-lik and lowest AIC values.

The dependence parameter of the Student-*t* copula is significant at the 1% threshold level and ranges from 0.100 (China-gold) to 0.266 (South Africa-gold). The low magnitude and positivity of the dependence parameter supports the hypothesis of gold as a diversifier for portfolios of stocks in the BRICS countries. As expected, the diversifying potential of gold is the lowest in South Africa given its dependence on mining sector, where gold exports and industry play an important role. In fact, this country is the first-largest gold producer in Africa and gold is its main export product with a share of 11.2% of total exports in 2014.[6] South Africa also holds about 50% of the world's gold resources according to the US Geological Survey estimates in 2002. We also find some evidence of asymmetric dependence with the SJC copula as the lower tail dependence parameter is greater than the upper tail dependence.

[Insert Table 3 about here]

[Insert Figures 5–6–7 about here]

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[6] http://atlas.media.mit.edu/en/profile/country/zaf/

Panel B of Table 3 presents the estimation results for the time-varying copulas which allow the dependence parameter to change through time with respect to market conditions (normal times versus crisis times). Figures 5–7 illustrate that copula parameters change over time. For example, the dependence parameter of the rotated Gumbel copula fluctuates within the interval (0.00–1.46) for Brazil-gold, (0.02–1.38) for Russia-gold, (1.02–1.28) for India-gold, and (1.08–1.82) for South Africa-gold. Notably, the rotated Gumbel is found, based on the AIC and maximum log-likelihood scores, as the best-suited time-varying copula model for capturing the dynamic changes in the conditional dependence structure between gold and stock markets. The relevance of the time-varying rotated Gumbel copula indicates that gold-stock dependence is higher during bearish periods than during bullish periods. This evidence thus does not support the safe haven role of gold which has been found by earlier studies for developed and emerging markets (e.g., Baur and Lucey, 2010; Beckmann et al., 2015), while it is still possible to obtain diversification benefits through including gold into stock portfolios given the low degree of dependence over time.

Finally, the results in Table 3 reveal that time-varying copulas do not always provide better fits to data than static copulas, based on the log-lik and AIC criteria. The best-fitted static copula, the Student-*t*, effectively outperforms all the time-varying copula models, except for the South Africa-gold pair when the rotated Gumbel copula is used.

5. CONCLUSION

In this paper, we extend the recent literature focusing on the role of gold for portfolio hedging and diversification, while shifting attention to the heterogeneous BRICS stock markets. While these markets have low correlations with developed markets and provide global investors with high returns spurred by high economic growth rates, they are becoming more sensitive and vulnerable to external shocks given their increasing integration with the rest of the world through both financial and trade links. The contagious effects of the US subprime crisis and the global financial crisis have prompted global investors to seek diversification, hedging, and safe haven op-

portunities in alternative asset classes including particularly gold. Our work addresses the hypotheses of gold as a hedge, a diversifier and a safe haven by making use of the continuous wavelet transform and the copula functions. This methodological framework allows us to measure not only the time-varying co-movement between gold and BRICS stock markets across frequencies (i.e., investigation of hedging versus diversifier potential), but also their conditional dependence structure in various market conditions such as normal and crisis times (i.e., investigation of hedging and diversifier versus safe haven properties). A frequency-domain test was also used as a preliminary analysis to show evidence of timescale causal interactions.

In addition to the existence of the two-way causality linkages across frequencies, our results document timescale and time-varying co-evolvement patterns between the two markets, with several periods of concentrated extreme variations. The degree of gold-stock market synchronization is however low in short and medium horizons, and but experiences sharp increase over the long run. The leading effect of gold market over the stock markets was also found during the recent global financial crisis. We also find evidence of time-varying, positive and asymmetric dependence between gold and stock markets, with the dependence level being higher during bad times than during good times.

Overall, our findings from a nonlinear wavelet-copula framework imply that the diversifying potential of gold tends to reduce in the long run, which seems to be consistent with the view that gold is becoming an integrated part of asset portfolios and that global investors adjust their portfolios with a close look at gold market fluctuations. Also, they clearly support the hypothesis of gold as a diversifier in both normal and bear markets for stocks in the BRICS countries, but not a hedge and a safe haven. This result is not surprising because the accelerated financialization of commodity markets, including the gold market, has significantly eased the investments in gold, making the gold asset behave more and more like stocks.

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TABLE 1. DESCRIPTIVE STATISTICS.

	Gold	Brazil	Russia	India	China	S. Africa
Mean(%)	0.039	0.027	0.023	0.030	0.025	0.028
Standard deviation	0.012	0.022	0.026	0.018	0.019	0.018
Risk-adjusted return (%)	3.250	1.227	0.885	1.667	1.316	1.556
Skewness	−0.279	−0.248	−0.522	−0.136	−0.003	−0.333
Kurtosis	8.854	10.208	14.338	10.271	8.598	7.748
J–B	5478.87^{+++}	8270.66^{+++}	20543.78^{+++}	8389.24^{+++}	4965.59^{+++}	3641.95^{+++}
Q(12)	27.95^{+++}	55.89^{+++}	49.78^{+++}	71.14^{+++}	31.23^{+++}	41.61^{+++}
Q^2(12)	315.96^{+++}	3771.09^{+++}	1846^{+++}	790.62^{+++}	2333.04^{+++}	2488.19^{+++}
ARCH(12)	14.98^{+++}	145.09^{+++}	68.94^{+++}	31.15^{+++}	81.47^{+++}	83.28^{+++}
Correlation versus Gold	1	0.15	0.12	0.11	0.09	0.28
Obs.	3803	3803	3803	3803	3803	3803

Notes: The risk-adjusted return is the ratio of mean to standard deviation. J–B, Q(12), Q^2(12) and ARCH(12) are the empirical statistics of the Jarque–Bera test for normality, Ljung–Box test for autocorrelation with 12 lags in returns, and Ljung–Box test for autocorrelation with 12 lags in squared returns, and Engle (1982) test for ARCH effects with 12 lags, respectively. $^{+++}$ indicates the rejection of the null hypothesis of normality, independence, and conditional homoscedasticity at the 1% significance level.

TABLE 2. GJR–GARCH PARAMETER ESTIMATION & DIAGNOSTICS.

Panel A: Estimation results of GARCH

	Brazil	Russia	India	China	South Africa	Gold
Parameter estimates-mean equations						
Const(m)(%)	0.0004^{*}	0.0010^{***}	0.0008^{***}	0.0005^{**}	0.055^{**}	0.0006^{***}
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
AR(1)	0.082^{***}	0.050^{***}	0.085^{***}	0.052	0.036^{**}	-0.044^{***}
	(0.015)	(0.016)	(0.016)	(0.015)	(0.016)	(0.014)
Parameter estimates–GARCH process						
Const(v)(10^{-4})	0.082^{***}	0.082^{***}	0.087^{***}	0.032^{***}	0.071^{***}	0.009^{***}
	(0.029)	(0.021)	(0.017)	(0.009)	(0.016)	(0.003)
ARCH(α)	0.009	0.064^{***}	0.041^{***}	0.024^{***}	0.015^{*}	0.057^{***}
	(0.007)	(0.012)	(0.010)	(0.006)	(0.008)	(0.010)
GARCH (β)	0.918^{***}	0.888^{***}	0.852^{***}	0.924^{***}	0.901^{***}	0.920^{***}
	(0.018)	(0.012)	(0.017)	(0.009)	(0.013)	(0.006)
GJR(γ)	0.100^{***}	0.070^{***}	0.148^{***}	0.080^{***}	0.111^{***}	0.027^{***}
	(0.020)	(0.018)	(0.027)	(0.017)	(0.019)	(0.011)
Student–df	9.255^{***}	5.517^{***}	7.168^{***}	7.014^{***}	11.859^{***}	4.171^{***}
	(1.293)	(0.502)	(0.842)	(0.802)	(1.969)	(0.328)
Log (L)	9737.00	9455.70	10629.45	10460.66	10426.7	12025.95
Panel B: Diagnostic tests						
Skewness	–0.249	–0.392	–0.057	–0.087	–0.208	–0.105
Kurtosis	1.105	2.956	2.378	1.034	0.610	6.577
AIC	–5.118	–4.969	–5.593	–5.497	–5.479	–6.320
SIC	–5.106	–4.957	–5.582	–5.486	–5.468	–6.309
Q(20)	20.31	16.05	29.42	32.36^{++}	23.77	17.29
Q^2(20)	15.85	12.31	33.14^{++}	13.99	28.46^{+}	8.56
ARCH(10)	0.93	0.66	1.34	0.49	0.52	0.59
J–B	202.55^{+++}	1482.70^{+++}	897.31^{+++}	177.44^{+++}	86.62^{+++}	6863.60^{+++}

Notes: This table reports the estimates of the GJR–GARCH models for each of the return series. Standard errors are in parentheses. *Const(m)* and *Const(v)* refer to the constant terms in the mean and variance equations. *, ** and *** indicate significance at the 10%. 5% and 1% threshold levels, respectively. J–B, Q(20), Q^2(20) and ARCH(10) are the empirical statistics of the Jarque–Bera test for normality, Ljung–Box test for autocorrelation with 20 lags in returns, Ljung–Box test for autocorrelation with 20 lags in squared returns, and Engle (1982) test for ARCH effects with 10 lags, respectively. $^{+}$, $^{++}$, and $^{+++}$ indicate the rejection of the null hypothesis of normality, independence, and conditional homoscedasticity at the 10%, 5%, and 1% threshold levels, respectively.

TABLE 3. ESTIMATION RESULTS CONSTANT AND TIME-VARYING COPULA MODELS.

Panel A: Time-invariant Copulas

	Brazil	Russia	India	China	South Africa
	Normal copula				
ρ	0.148	0.133	0.113	0.097	0.265
LogLik	−42.497	−34.284	−24.640	−18.252	−138.603
AIC	86.99	70.56	51.28	38.50	279.20
	Clayton copula				
ρ	0.199***	0.185***	0.155***	0.132***	0.370***
	(0.021)	(0.021)	(0.020)	(0.020)	(0.024)
LogLik	56.877	50.069	36.776	27.215	158.546
AIC	−111.73	−98.13	−71.55	−52.42	−315.09
	Rotated Clayton copula				
ρ	0.154***	0.129***	0.108***	0.084***	0.293***
	(0.021)	(0.020)	(0.020)	(0.019)	(0.023)
LogLik	33.286	24.358	17.829	11.092	100.099
AIC	−64.57	−46.716	−33.65	−20.18	−198.19
	Plackett copula				
θ	1.644***	1.541***	1.427***	1.358***	2.351***
	(0.084)	(0.080)	(0.072)	(0.068)	(0.114)
LogLik	45.304	34.304	23.695	18.316	138.501
AIC	−88.608	−66.60	−45.38	−34.63	−275.00
	Frank copula				
λ	0.915***	0.795***	0.662	0.585***	1.717***
	(0.100)	(0.101)	(1.001)	(0.099)	(0.199)
LogLik	41.179	31.181	21.917	17.426	37.14
AIC	−80.357	−60.36	−41.83	−32.85	−72.28
	Gumbel copula				
δ	1.102***	1.100***	1.100***	1.100***	1.191***
	(0.012)	(0.019)	(0.019)	(0.019)	(0.014)
LogLik	51.829	39.598	27.041	11.236	141.822
AIC	−101.65	−77.19	−52.08	−20.47	−281.64
	Rotated Gumbel copula				
δ	1.114***	1.105***	1.100***	1.100***	1.212***
	(0.012)	(0.011)	(0.019)	(0.019)	(0.014)
LogLik	70.897	60.039	43.410	29.928	184.126
AIC	−139.79	−118.07	−84.81	−57.85	−366.25
	Student-*t* copula				
ρ	0.152***	0.135***	0.113***	0.100***	0.266***
	(0.018)	(0.018)	(0.017)	(0.016)	(0.017)
υ	4.984***	0.548***	6.159***	8.723***	4.613***
	(0.504)	(0.599)	(0.766)	(1.439)	(0.428)
LogLik	106.694	87.556	66.800	41.222	217.664
AIC	−209.38	−171.11	−129.59	−78.44	−431.32
	Symmetrized Joe–Clayton (SJC) copula				
λ_U	0.013	0.002	0.001	0.000	0.069***
	(0.013)	(0.005)	(0.002)	(0.000)	(0.019)
λ_L	0.072***	0.073***	0.054***	0.041**	0.176***
	(0.021)	(0.019)	(0.018)	(0.018)	(0.019)
LogLik.	69.477	58.157	42.756	30.770	190.895
AIC	−134.95	−112.31	−81.50	−57.53	−377.78

Panel B: Time-varying Copulas

	Brazil	Russia	India	China	South Africa
			Time-varying Normal copula		
Ψ_0	0.001	0.001	0.009^{**}	0.197	0.018
	(0.001)	(0.001)	(0.004)	(0.283)	(0.019)
Ψ_1	0.020^{***}	0.018^{***}	0.032^{***}	0.001	0.032^{**}
	(0.004)	(0.004)	(0.010)	(0.967)	(0.013)
Ψ_2	2.002^{***}	2.001^{***}	1.903^{***}	0.0002	1.951^{***}
	(0.006)	(0.006)	(0.044)	(0.995)	(0.086)
LogLik	67.096	58.991	39.165	18.252	149.677
AIC	−128.18	−111.97	−72.32	−30.49	−293.34
			Time-varying rotated Gumbel Copula		
Ψ_0	1.324^{**}	0.466^{**}	-0.634^{***}	2.225^{***}	−0.140
	(0.527)	(0.745)	(0.237)	(0.101)	(0.105)
Ψ_1	−0.352	0.171	0.951^{***}	-1.852^{***}	0.621^{***}
	(0.402)	(0.548)	(0.175)	(0.122)	(0.057)
Ψ_2	-1.893^{***}	-1.033^{**}	-0.320^{*}	0.098^{**}	-0.536^{***}
	(0.264)	(0.444)	(0.157)	(0.049)	(0.131)
LogLik	96.014	80.375	52.475	33.816	221.293
AIC	−186.02	−154.74	−98.944	−61.62	−436.58
			Time-varying SJC copula		
Ψ_0	1.654	3.241^{**}	−1.031	-13.681^{***}	1.719
	(1.308)	(1.582)	(3.166)	(1.000)	(1.238)
Ψ_1	-16.774^{***}	-25.000^{***}	−14.404	−0.001	-15.384^{***}
	(4.860)	(6.627)	(12.328)	(1.000)	(4.300)
Ψ_2	−5.045	-5.037^{*}	−0.003	−0.000	−1.167
	(4.452)	(2.750)	(1.004)	(1.000)	(2.310)
Ψ_3	0.527	1.547^{*}	1.488	-3.384^{***}	-1.399^{***}
	(1.549)	(0.944)	(1.382)	(0.600)	(0.331)
Ψ_4	-10.917^{**}	-13.099^{***}	-14.333^{***}	−0.057	-2.754^{***}
	(5.207)	(2.936)	(5.289)	(1.000)	(0.963)
Ψ_5	1.086	−3.941	−2.524	−0.020	3.604^{***}
	(2.454)	(2.591)	(2.719)	(0.999)	(0.468)
LogLik	93.101	78.264	49.803	30.076	228.886
AIC	−174.17	−144.50	−87.58	−48.13	−445.75

Notes: The table reports the maximum likelihood estimates for the different copula models. Standard error values are presented in parentheses and Akaike Information Criterion (AIC) values adjusted for small-sample bias are provided for the different copula models. The minimum AIC value (in bold) indicates the best copula fit. *, ** and *** indicate significance at the 10%. 5% and 1% threshold levels, respectively.
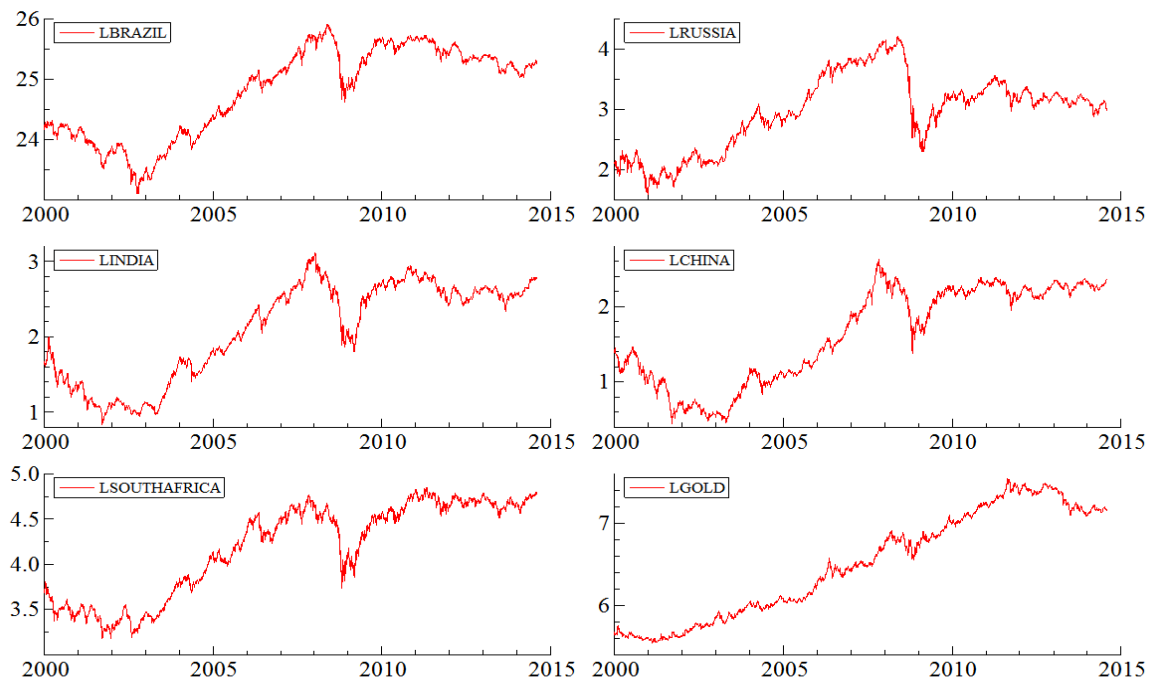
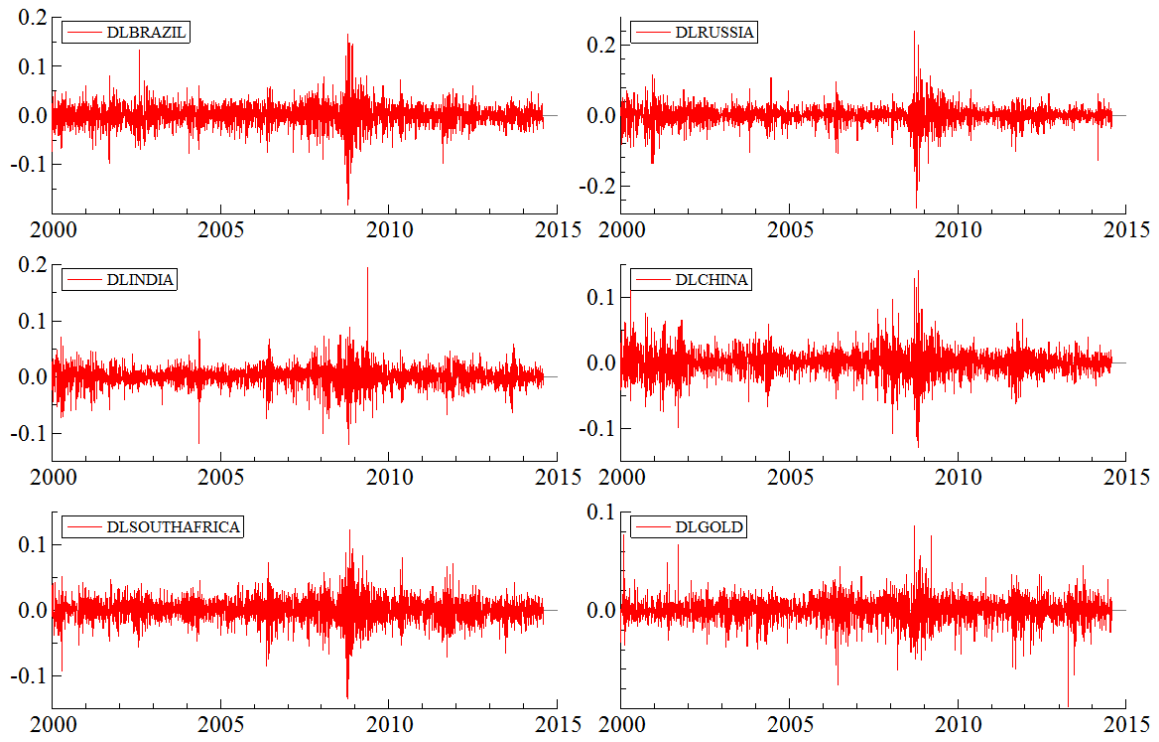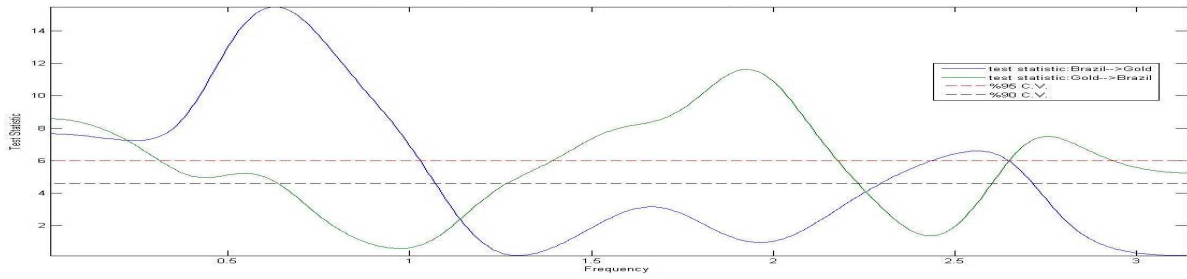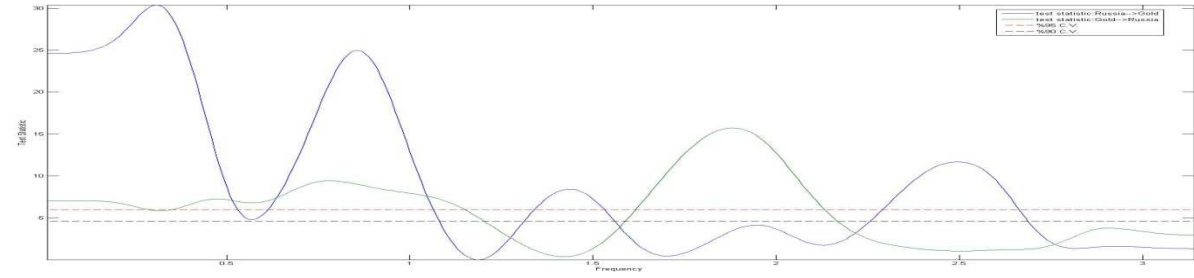**Fig. 1.** Log Price Dynamics of BRICS Stock Markets and Gold Futures

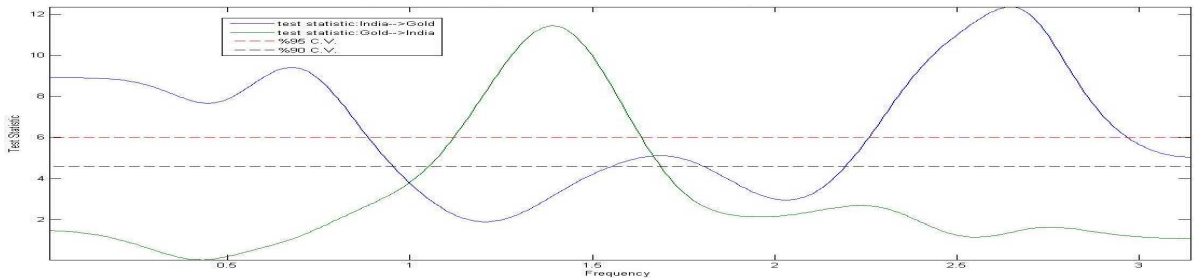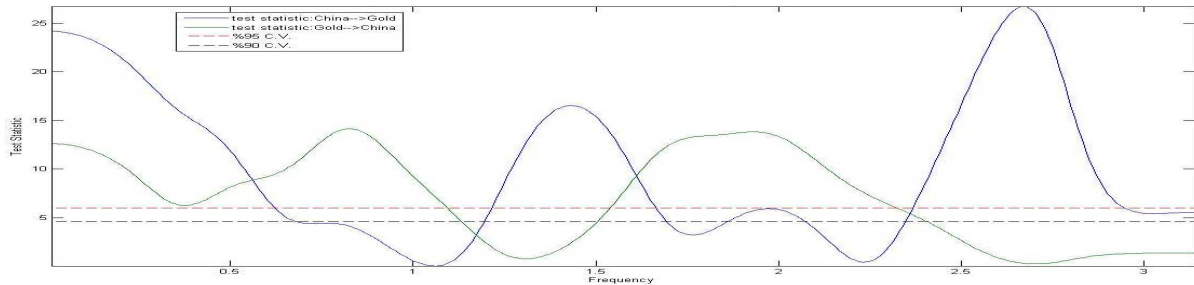**FIG. 2.** DYNAMICS OF BRICS MARKET AND GOLD FUTURES RETURNS

Brazil-Gold

Russia-Gold

India-Gold

China-Gold
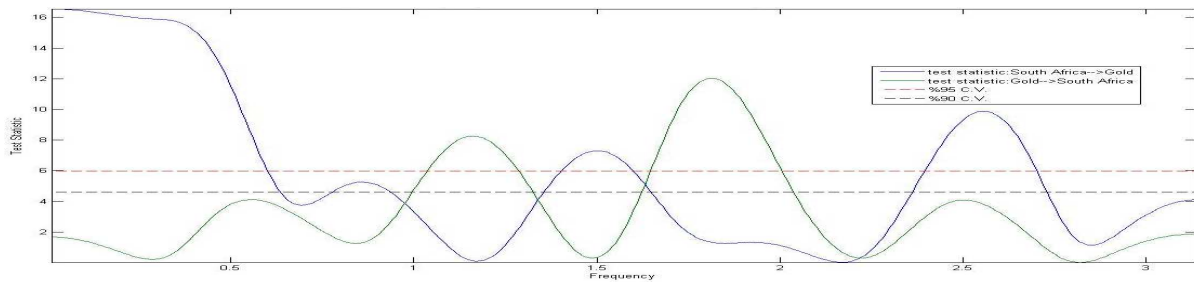

South Africa-Gold

FIG. 3. FREQUENCY-DOMAIN CAUSALITY BETWEEN THE BRICS MARKETS AND GOLD FUTURES

Notes: The frequency ϑ on the horizontal axis can be translated into a cycle (or periodicity) of T months as denoted in the formula $T = 2\pi / \vartheta$. Four bands or time horizons are considered: very short horizons with $(0, 0.5)$, short-run horizons $(0.5, 1.5)$, medium-run with $(1.5, 2.5)$ and longest periods with a range of $(2.5, \pi)$. The short-term fluctuations are presented at the right-end whilst the long-run frequencies at the left end. Dotted lines denote the 5% and 10% levels of significance. The test statistics are presented in the vertical axis.
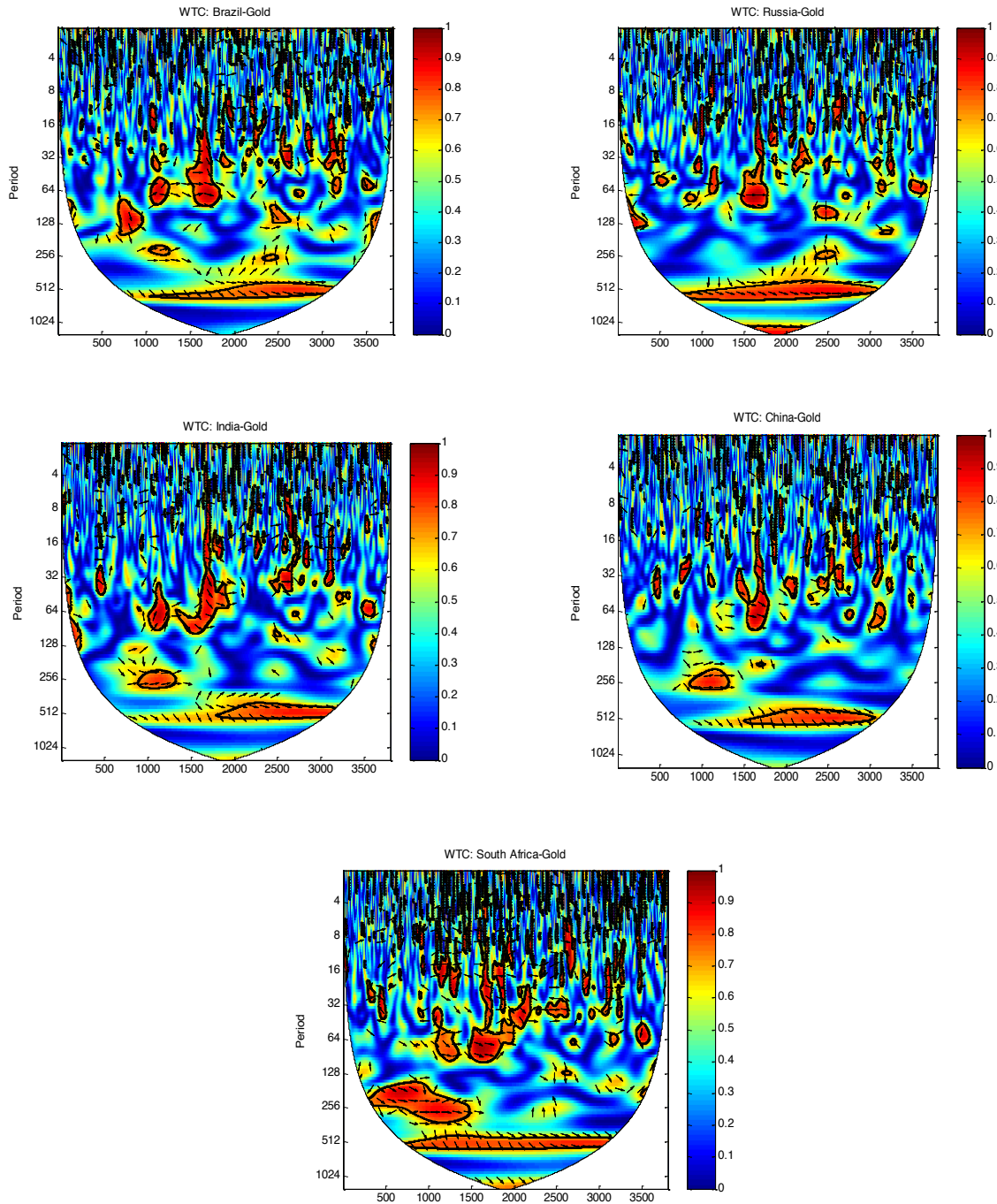
FIG. 4. CROSS-WAVELET COHERENCE BETWEEN THE BRICS MARKETS AND GOLD FUTURES
Notes: Phase arrows indicate the direction of co-movement among the returns series of the BRICS' equity markets and Gold pairwise. Arrows pointing to the right signify perfectly phased variables. The direction "right-up" indicates lagging gold market, while the "right-down" direction indicates leading gold market over the BRICS stock markets. Arrows pointing to the left signify out-of-phase variables. The direction "left-up" indicates leading Gold, whilst the "left-down" direction indicates a lagging Gold market. In-phase variables represent a cyclical relationship and out-of-phase (or anti-phase) variables show anti-cyclical behavior. The thick black contour lines indicate the 5% significance intervals estimated from Monte Carlo simulations with phase-randomized surrogate series. The cone of influence, which marks the region affected by edge effects, is shown with a lighter shade black line. The color legend for spectrum power ranges from Blue (low power) to Red (high power). Y-axis measures frequency (scale) and X-axis represents the time period studied ranging from 500, 1000, 1500, 2000, 2500, 3000 to 3500 observations. The corresponding dates are $2001M_{12}D_{03}$, $2003M_{11}D_{03}$, $2005M_{10}D_{03}$, $2007M_{09}D_{03}$, $2009M_{08}D_{03}$, $2011M_{07}D_{04}$, and $2013M_{06}D_{03}$ respectively. The starting and ending dates are $2000M_{01}D_{04}$ and $2014M_{07}D_{31}$, respectively.

Brazil

Russia

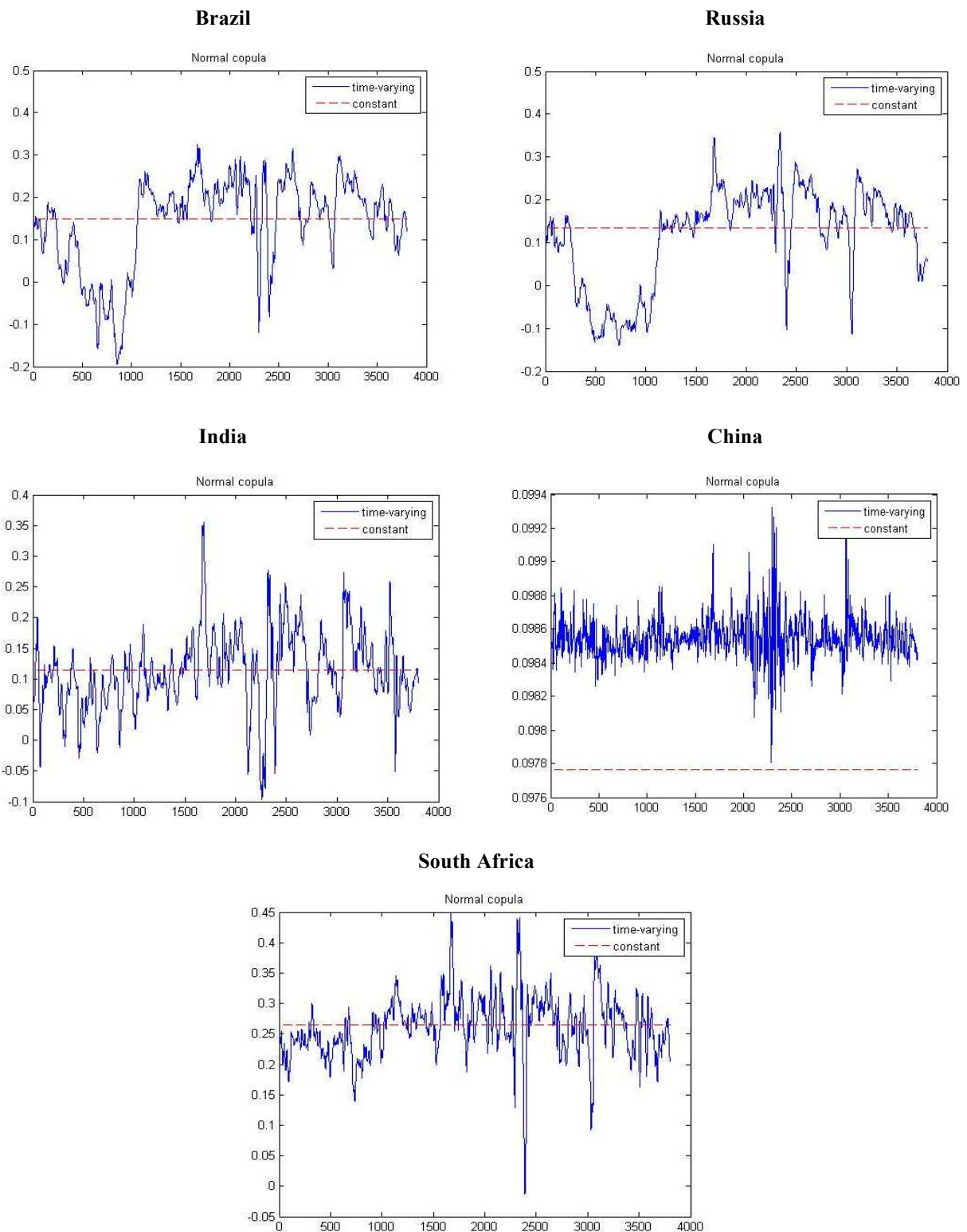

India

China

South Africa

Fig. 5. TVP-Normal Copula Dependence

Notes: The *X*-axis the time period is divided into 500, 1000, 1500, 2000, 2500, 3000 to 3500 daily observations corresponding to the following dates: $2001M_{12}D_{03}$, $2003M_{11}D_{03}$, $2005M_{10}D_{03}$, $2007M_{09}D_{03}$, $2009M_{08}D_{03}$, $2011M_{07}D_{04}$, and $2013M_{06}D_{03}$, respectively. The starting and ending dates are $2000M_{01}D_{04}$ and $2014M_{07}D_{31}$, respectively.

Brazil

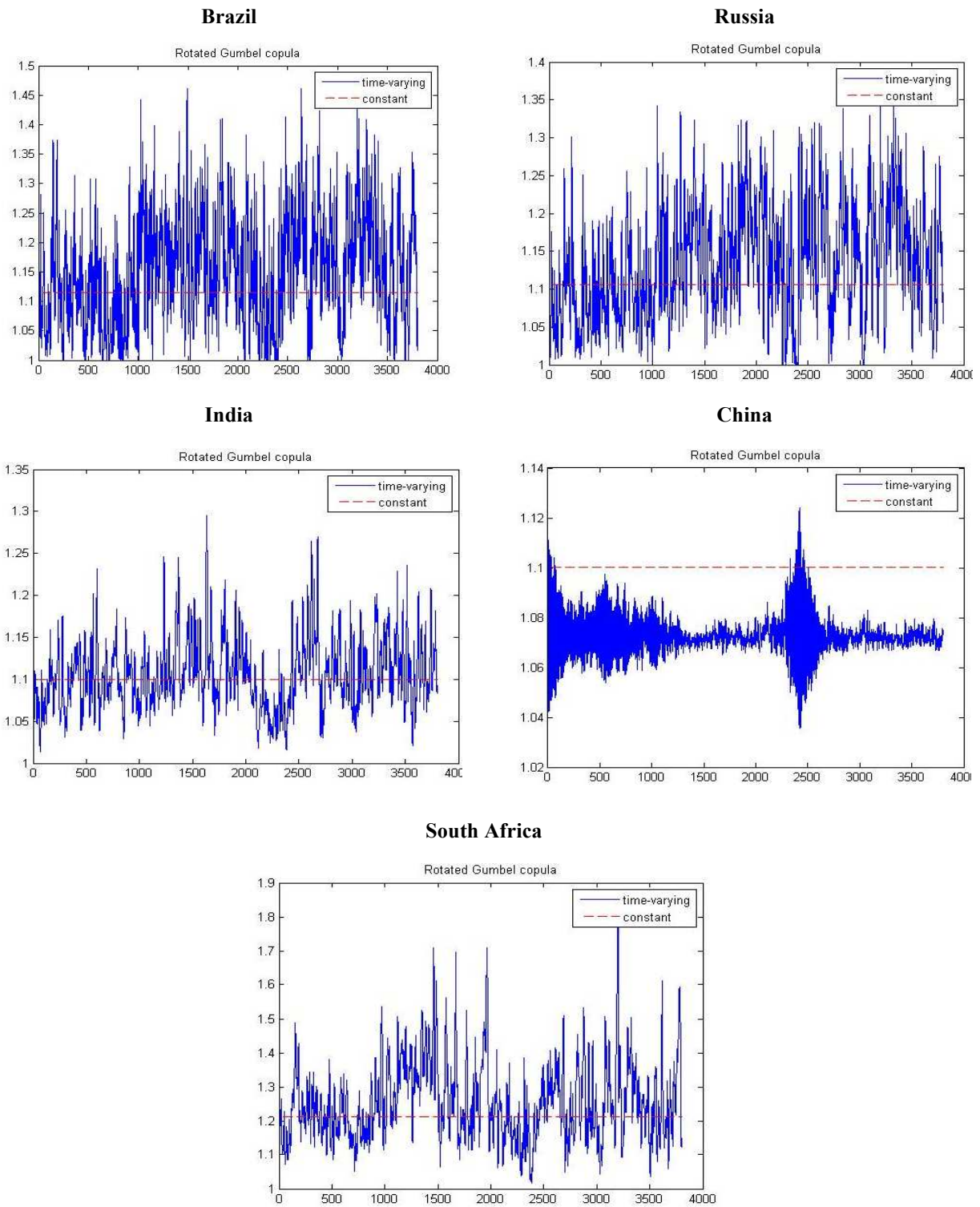**Russia**

India

China

South Africa

FIG. 6. TVP-ROTATED GUMBEL COPULA DEPENDENCE

Notes: The *X*-axis the time period is divided into 500, 1000, 1500, 2000, 2500, 3000 to 3500 daily observations corresponding to the following dates: $2001M_{12}D_{03}$, $2003M_{11}D_{03}$, $2005M_{10}D_{03}$, $2007M_{09}D_{03}$, $2009M_{08}D_{03}$, $2011M_{07}D_{04}$, and $2013M_{06}D_{03}$, respectively. The starting and ending dates are $2000M_{01}D_{04}$ and $2014M_{07}D_{31}$, respectively.

Brazil

Russia

India

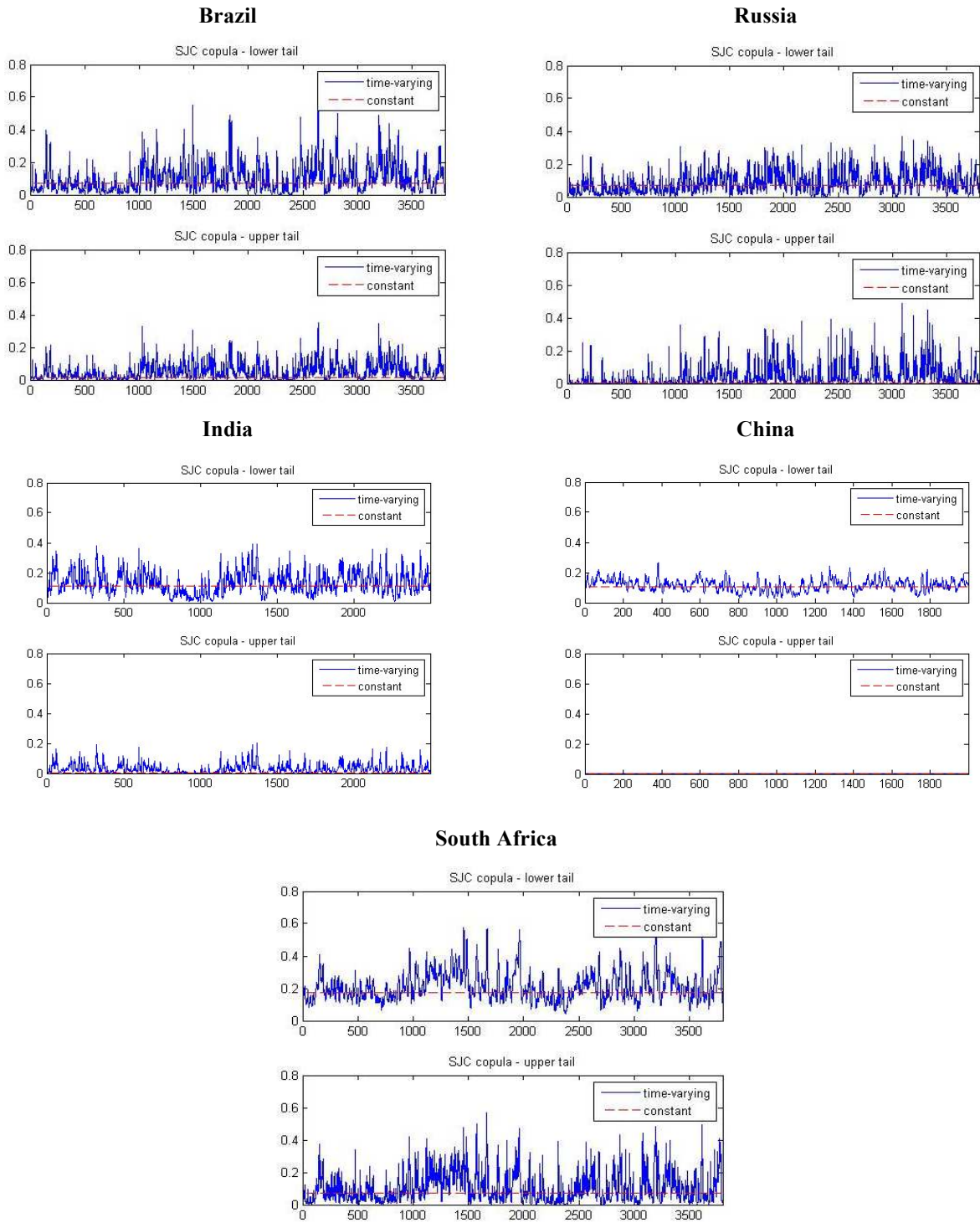**China**

South Africa

FIG. 7. TVP-SJC COPULA DEPENDENCE

Notes: The *X*-axis the time period is divided into 500, 1000, 1500, 2000, 2500, 3000 to 3500 daily observations corresponding to the following dates: $2001M_{12}D_{03}$, $2003M_{11}D_{03}$, $2005M_{10}D_{03}$, $2007M_{09}D_{03}$, $2009M_{08}D_{03}$, $2011M_{07}D_{04}$, and $201M_{06}D_{03}$., respectively. The starting and ending dates are $2000M_{01}D_{04}$ and $2014M_{07}D_{31}$, respectively (for Brazil, Russia and South Africa). For the TVP-SJC in particular the time sample estimation for India is $2005M_{01}$ and $2014M_{12}$ whilst for China $2007M_{01}$ to $2011M_{12}$ respectively.