Journal of Banking & Finance 62 (2016) 76–96

Contents lists available at ScienceDirect

Journal of Banking & Finance

journal homepage: www.elsevier.com/locate/jbf

Downside and upside risk spillovers between exchange rates and stock prices

Juan C. Reboredo [a,*], Miguel A. Rivera-Castro [b], Andrea Ugolini [b,c]

[a] Department of Economics, Universidade de Santiago de Compostela, Santiago de Compostela, Spain
[b] Post-Graduate Programme in Management, UNIFACS, Rúa Dr. José Peroba 251, 41770-235 Salvador, Brazil
[c] Dipartimento di Statistica, Informatica, Applicazioni "G. Parenti", Università di Firenze, Italy

ARTICLE INFO

Article history:
Received 22 December 2014
Accepted 16 October 2015
Available online 23 October 2015

JEL classification:
C58
F31
G15

Keywords:
Stock prices
Exchange rates
Spillover
Downside risk
Upside risk
Copulas
Emerging markets

ABSTRACT

We examined downside and upside risk spillovers from exchange rates to stock prices and vice versa for a set of emerging economies. We characterized the dependence structure between currency and stock returns using copulas and computed downside and upside value-at-risk and conditional value-at-risk. We documented a positive relationship between stock prices and currency values in emerging economies with respect to the US dollar and the euro, with downside and upside spillover risk effects transmitted both ways. Finally, we also documented asymmetries in upside and downside risk spillovers and asymmetric differences in the size of risk spillovers when the domestic currency values against the US dollar and the euro. Our results, consistent with flight-to-quality phenomena, have implications for downside and upside risk management of international investor portfolios in emerging markets.

1. Introduction

Exchange rates and stock prices are two crucial macro finance variables that are intrinsically linked. Exchange rate movements have effects on stock prices given that an appreciation (depreciation) in a domestic currency reduces (increases) the international competitiveness of domestic firms and their cash flows, thereby reducing (increasing) domestic stock prices. Similarly, stock price changes impact exchange rates, since an increase in domestic stock prices triggers currency adjustments to accommodate variations in demand and supply for domestic and foreign assets included in internationally diversified portfolios. Therefore, understanding how exchange rates and stock markets co-move is an important issue for international investors and policy makers in equal measure. In particular, the spillover effect of extreme upward or downward exchange rate movements on stock market performance and vice versa has important implications in terms of risk management and trading and hedging strategies for international portfolios. The aim of this paper is to quantify and test for spillover risk effects between stock and exchange markets in emerging economies.

The extant empirical literature offers extensive evidence regarding average stock and exchange rate relationships (see the literature review below). However, few studies have examined the dependence structure (in particular, tail dependence) between stock prices and exchange rates (see Ning, 2010; Michelis and Ning, 2010; Lin, 2011; Wang et al., 2013). Moreover, to our knowledge no study to date has analyzed co-movement between stock and exchange rate markets, paying specific attention to quantifying and testing for the impact of upward and downward movements in exchange rates on upside and downside risk in stock markets and vice versa. This issue is of particular interest to investors who want to protect a diversified portfolio against the adverse effects of extreme market movements. It is also of interest to policy makers, as specific shocks in foreign exchange markets could have ramifications for domestic stock markets and may affect capital inflows, which ultimately may affect economic growth. In studying co-movement and spillover risk effects between the stock and

* Corresponding author at: Universidade de Santiago de Compostela, Departamento de Fundamentos del Análisis Económico, Avda. Xoán XXIII, s/n, 15782 Santiago de Compostela, Spain. Tel.: +34 881811675; fax: +34 981547134.
E-mail address: juancarlos.reboredo@usc.es (J.C. Reboredo).

http://dx.doi.org/10.1016/j.jbankfin.2015.10.011
0378-4266/

exchange rate markets, we attempt to add to the existing empirical literature regarding this relationship in two ways.

First, we studied co-movement between stock and exchange rate markets using static and dynamic copula functions, which enable us to assess both average movements across marginals and joint extreme upward and downward movements. On the basis of copula information, we then evaluated the impact of downside and upside risk spillover from one market to the other by computing the downside and upside conditional value-at-risk (CoVaR) (Adrian and Brunnermeier, 2011; Girardi and Ergün, 2013) in the stock and exchange rate markets. CoVaR captures spillover effects between markets by providing the value-at-risk (VaR) of one market conditional on the fact that the other market is under financial distress as measured by its VaR. We assessed spillover effects by testing for significant differences between CoVaR and VaR values using the Kolmogorov–Smirnov (KS) bootstrapping test as proposed by Abadie (2002) and applied by Bernal et al. (2014). Thus, our methodological approach has the advantage of flexibly and fully characterizing the dependence structure between stock and exchange rate markets and providing information on downside and upside spillover effects through the CoVaR, computed using the computationally tractable two-step copula procedure described in Reboredo and Ugolini (2015) for downside CoVaR.

Second, we studied downside and upside spillover effects between stock and exchange rate returns by examining dependence for a broad set of currency–equity pairs for emerging economies (Brazil, Chile, Colombia, India, Mexico, Russia, South Africa and Turkey)—given that these financial markets are sensitive to speculative attacks, to changes in policies with the aim of managing exchange rates and to capital inflows and outflows responding to currency and economic development uncertainties. As trading and capital flows in these economies are mainly denominated in dollars (USD) and euros (EUR), we considered rates for these two currencies against local currencies. Our evidence for the period April 2001 to November 2014 indicates average co-movement between stock and exchange rate markets: emerging economy currencies appreciated (depreciated) as stock market prices rose (fell), consistent with the fact that bullish (bearish) stock markets attract capital inflows as foreign investor demand for local assets increases (decreases)—thus ultimately increasing (reducing) the value of the home currency. We also found evidence of downside and upside risk spillover effects from exchange rates to stock markets and vice versa, given that the downside and upside CoVaR values were, in general, significantly different from the VaR values. In examining asymmetries, we found consistent evidence of asymmetric downside and upside spillovers, with the downside effects greater than the upside effects. We also found asymmetries in spillovers using different currency denominations: spillovers from and to the USD were greater than for the EUR, which may be explained by the fact that the USD plays a more crucial role in trade and finance in emerging economies. Our downside risk results are consistent with flight-to-quality and our analysis has practical implications for the management of downside and upside risk in international investor portfolios that include emerging market assets.

The remainder of the paper is laid out as follows: in Section 2 we review the literature on the relationship between stock prices and exchange rates; in Section 3 we outline the methodological approach to characterizing dependence and the CoVaR; in Section 4 we present our data and in Section 5 we discuss the results. Finally, Section 6 concludes the paper.

2. Literature review

The relationship between stock prices and exchange rates is well established at the theoretical level. The model of exchange rates proposed by Dornbusch and Fischer (1980) focuses on the effects of exchange rate movements on international competitiveness and trade balances. Thus, depreciation (appreciation) of local currency improves (deteriorates) the international competitiveness of local firms and their cash flows, thereby increasing (reducing) stock prices. Other exchange rate models (Branson, 1993; Frankel, 1983) focus on the impact of stock markets on exchange rates: a reduction in stock prices discourages capital inflows as foreign investor demand for local assets decreases, thereby reducing the value of the local currency. Similarly, since changes in the value of local assets can rebalance international investor portfolios, capital flows generate dependence between stock and currency markets (Hau and Rey, 2006; Pavlova and Rigobon, 2007). Furthermore, monetarist models of exchange rate determination (Gavin, 1989) state that changes in the value of stocks may affect exchange rates through the demand for money.

The relationship between stock prices and exchange rates has empirically been extensively examined. Some studies of causality provide evidence, differing across countries, of no causality, unidirectional causality or bivariate causality.[1] Yet other studies have examined the structure of dependence between stock and exchange rate markets. Ning (2010) used different static copulas to characterize dependence between the equity and foreign exchange rate markets for six industrialized countries in the periods before and after the launch of the EUR, finding evidence of symmetric tail dependence. Contrarily, Michelis and Ning (2010) found evidence of asymmetries between Canadian stock returns and the exchange rate against the USD. Also, Lin (2011) examined copula dependence in five East Asian economies, finding evidence of tail independence and asymmetric tail dependence. Finally, Wang et al. (2013) studied dependence between stock and foreign exchange markets in six major industrial countries using a Markov switching copula, finding that dependence and tail dependence were asymmetric in regimes where local currency values against the USD and stock returns were negatively correlated, but symmetric in regimes where local currency values against the USD and stock returns were positively correlated.

Another strand of the literature has examined the relationship between currency and stock returns through the impact on currency markets of capital flows generated by changes in international equity portfolio investments. Thus, Froot et al. (2001), Griffin et al. (2004) and Richards (2005) reported a positive relationship between equity returns and capital inflows—in particular in emerging markets—that generated positive links between equity and local currency values in emerging economies. More recently, Cho et al. (2016) reported that capital inflows and outflows in emerging economies were sensitive to equity market conditions, especially in downturns, when capital movements induced by flight-to-quality generated positive correlations between equity and local currencies.

All the above-mentioned empirical studies consider mean or variance effects in their identification of causal effects between stock prices and exchange rates or consider symmetric effects in the tail dependence structure between equity and exchange rates. However, no study—as far as we are aware—has considered the relationship between stock and exchange rate markets in terms of downside/upside spillover effects of one market on another market—very crucial in terms of international portfolio risk management. To fill this gap, we characterize dependence between stock and exchange rate returns for a broad set of emerging countries. We use static and dynamic copulas, as these offer information on

[1] See, e.g., Abdalla and Murinde (1997), Chow et al. (1997), Ajayi et al. (1998), Granger et al. (2000), Nieh and Lee (2001), Yang and Doong (2004), Phylaktis and Ravazolo (2005), Aloui (2007), Pan et al. (2007), Diamandis and Drakos (2011), Lin (2012)

the static or time-varying dependence features without requiring a proxy for the unobservable state with an instrument, as is the case for switching copulas (see Wang et al., 2013). Furthermore, from the static and dynamic copulas we can provide quantitative evidence and tests for the impact of extreme movements in one market on another market using the VaR and the CoVaR measures.

3. Methodological issues

3.1. Dependence

We characterized the dependence structure between stock prices and stock returns using copulas[2] because these provide information on average dependence and dependence at the tails of the joint distribution. Given two random variables X and Y with distribution function $F_{XY}(x,y)$ and with marginal functions $F_X(x)$ and $F_Y(y)$, a copula is a multivariate function that couples the marginal distribution functions to represent the joint distribution function (Sklar, 1959) as:

$$F_{XY}(x,y) = C(F_X(x), F_Y(y)), \tag{1}$$

where $C(u,v)$ for $u = F_X(x)$ and $v = F_Y(y)$ is a (bivariate) copula function that is uniquely determined for the ranks $\mathrm{Ran}F_X \times \mathrm{Ran}F_Y$ when margins are continuous. Moreover, the joint density $f_{XY}(x,y)$ can be obtained from the copula density $c(u, v)$ as:

$$f_{XY}(x,y) = c(u, v) f_X(x) f_Y(y), \tag{2}$$

where $c(u, v) = \partial^2 C(u, v)/\partial u \partial v$, and $f_X(x)$ and $f_Y(y)$ are the marginal densities of the X and Y variables, respectively. Thus, the joint density can be decomposed into its univariate marginal distributions and a copula that captures the dependence structure. Copulas provide modeling flexibility in characterizing dependence because they allow separate modeling of the marginal distributions and of the copula function characterizing dependence. A copula also allows us to measure the probability that two variables experience joint extreme upward or downward movements through upper (right) and lower (left) tail dependence, computed from the copula as:

$$\lambda_U = \lim_{u \to 1} \Pr\left[X \geqslant F_X^{-1}(u) | Y \geqslant F_Y^{-1}(u)\right] = \lim_{u \to 1} \frac{1 - 2u + C(u,u)}{1-u}, \tag{3}$$

$$\lambda_L = \lim_{u \to 0} \Pr\left[X \leqslant F_X^{-1}(u) | Y \leqslant F_Y^{-1}(u)\right] = \lim_{u \to 0} \frac{C(u,u)}{u}, \tag{4}$$

where $\lambda_U, \lambda_L \in [0,1]$. Lower (upper) tail dependence means that we have a non-zero probability of observing extremely small (large) values for one variable together with extremely small (large) values for another variable.

Table 1 includes different copula specifications that can capture different features of dependence between stock and exchange rate markets: the Gaussian copula with tail independence; the Student-t copula with symmetric tail dependence; the Gumbel copula with upper tail dependence and lower tail independence; the rotated Gumbel copula with lower tail dependence and upper tail independence; and the BB7 copula with differing upper and lower tail dependence. To account for time-varying dependence, we allowed the parameters of some copula specifications to change over time. Thus, the temporal dynamics of the correlation coefficient for the Gaussian and the Student-t was characterized using an autoregressive moving average process, namely an ARMA(1,q) (see Patton, 2006):

$$\rho_t = \Lambda\left(\psi_0 + \psi_1 \rho_{t-1} + \psi_2 \frac{1}{q}\sum_{j=1}^{q} \Phi^{-1}(u_{t-j}) \cdot \Phi^{-1}(v_{t-j})\right), \tag{5}$$

where $\Lambda(x) = (1 - e^{-x})(1 + e^{-x})^{-1}$ is the modified logistic transformation that keeps the value of ρ_t in (−1,1) and $\Phi^{-1}(x)$ is a standard normal quantile function that is substituted by $t_\upsilon^{-1}(x)$ for the Student-t copula. For the Gumbel and the rotated Gumbel the parameter dynamics was assumed to follow the ARMA(1,q) process given by:

$$\delta_t = \omega + \beta\delta_{t-1} + \alpha\frac{1}{q}\sum_{j=1}^{q}|u_{t-j} - v_{t-j}|. \tag{6}$$

The time-varying dependence for the BB7 copula parameters was assumed to follow the following dynamics:

$$\theta_t = \omega + \beta\theta_{t-1} + \alpha\frac{1}{q}\sum_{j=1}^{q}|u_{t-j} - v_{t-j}|,$$

$$\delta_t = \bar{\omega} + \bar{\beta}\delta_{t-1} + \bar{\alpha}\frac{1}{q}\sum_{j=1}^{q}|u_{t-j} - v_{t-j}|. \tag{7}$$

The marginal densities of the stock and exchange rate returns (r_t) were characterized by an ARMA(p, q) model:

$$r_t = \phi_0 + \sum_{j=1}^{p}\phi_j r_{t-j} + \varepsilon_t - \sum_{i=1}^{q}\theta_i\varepsilon_{t-i}, \tag{8}$$

where p and q are non-negative integers and where ϕ_j and θ_i are the autoregressive (AR) and moving average (MA) parameters. $\varepsilon_t = \sigma_t z_t$, where σ_t^2 is the conditional variance that has dynamics as given by a threshold generalized autoregressive conditional heteroskedasticity (TGARCH) model:

$$\sigma_t^2 = \omega + \sum_{k=1}^{r}\beta_k\sigma_{t-k}^2 + \sum_{h=1}^{m}\alpha_h\varepsilon_{t-h}^2 + \sum_{h=1}^{m}\lambda_h 1_{t-h}\varepsilon_{t-h}^2, \tag{9}$$

where ω is a constant; σ_{t-k}^2 is the GARCH component; ε_{t-h}^2 is the ARCH component; $1_{t-h} = 1$ if $\varepsilon_{t-h} < 0$ and otherwise 0; and where λ captures asymmetric effects. When $\lambda > 0$ the future conditional variance will proportionally increase more following a negative shock than following a positive shock of the same magnitude. Note that when $\lambda = 0$, the volatility model in Eq. (9) is the GARCH model. z_t is an *i.i.d.* random variable with zero mean and unit variance that follows a Hansen's (1994) skewed-t density distribution that captures the fat tail and asymmetries in stock and exchange rate return distributions. It is specified as:

$$f(z_t;\upsilon,\eta) = \begin{cases} bc\left(1 + \frac{1}{\upsilon-2}\left(\frac{bz_t+a}{1-\eta}\right)^2\right)^{-(\upsilon+1)/2} & z_t < -a/b \\ bc\left(1 + \frac{1}{\upsilon-2}\left(\frac{bz_t+a}{1+\eta}\right)^2\right)^{-(\upsilon+1)/2} & z_t \geqslant -a/b \end{cases}, \tag{10}$$

where υ and η are the degrees of freedom parameter ($2 < \upsilon < \infty$) and the symmetric parameter ($-1 < \eta < 1$), respectively. The constants a, b and c are given by $a = 4\eta c(\frac{\upsilon-2}{\upsilon-1})$, $b^2 = 1 + 3\eta^2 - a^2$, $c = \Gamma(\frac{\upsilon+1}{2})/\sqrt{\pi(\upsilon-2)}\Gamma(\frac{\upsilon}{2})$. If $\eta = 0$ and $\upsilon \to \infty$, then the skewed-t converges to the standard Gaussian distribution, whereas if $\eta = 0$ and υ is finite, it converges to the symmetric Student-t distribution.

To estimate the copula and marginal density parameters, the log-likelihood function is decomposed (see Eq. (2)) as the sum of the log-likelihood function of the marginals plus the log-likelihood function of the copula. Consequently, we firstly estimated the parameters of the marginal distributions separately by maximum likelihood and then—in order to estimate copula parameters by maximizing the log-likelihood function—took the probability transform of the standardized marginal residuals $\hat{u}_t$ and $\hat{v}_t$ as pseudo-sample observations for the copula. This two-step procedure is called inference for margins (Joe and Xu, 1996). The number of lags in the mean and variance equations for each series was selected according to the Akaike information criteria (AIC) and

[2] For an introduction to copulas, see Joe (1997) and Nelsen (2006).

Table 1
Copula specifications.

Name	Copula	Parameter	Structure dependence
Gaussian	$C_N(u,v;\rho)=\Phi(\Phi^{-1}(u),\Phi^{-1}(v))$	ρ	No tail dependence. $\lambda_U=\lambda_L=0$
T-Student	$C_{ST}(u,v;\rho,\upsilon)=T(t_\upsilon^{-1}(u),t_\upsilon^{-1}(v))$	ρ,υ	Symmetric tail dependence: $\lambda_L=\lambda_U=2t_{\upsilon+1}(-\sqrt{\upsilon+1}\sqrt{1-\rho}/\sqrt{1+\rho})$
Gumbel	$C_G(u,v;\delta)=\exp\left(-((-\log u)^\delta+(-\log v)^\delta)^{1/\delta}\right)$	$\delta\geqslant 1$	$\lambda_L=0,\lambda_U=2-2^{1/\delta}$
Rotated Gumbel	$C_{RG}(u,v;\delta)=u+v-1+C_G(1-u,1-v;\delta)$	$\delta\geqslant 1$	$\lambda_L=2-2^{1/\delta},\ \lambda_U=0$
BB7	$C_{BB7}(u,v;\delta,\theta)=1-\left(1-\left[(1-(1-u)^\theta)^{-\delta}+(1-(1-v)^\theta)^{-\delta}-1\right]^{-1/\delta}\right)^{1/\theta}$	$\theta\geqslant 1,\delta>0$	$\lambda_L=2^{-1/\delta},\ \lambda_U=2-2^{1/\theta}$

Notes: This table reports the main features of the copula functions used in the empirical analysis. Further details can be found in Joe (1997) and Nelsen (2006). We also captured time-varying dependence by assuming that copula parameters change over time (see Eqs. (5)–(7)).

performance of the different copula models was evaluated using the AIC adjusted for small-sample bias, as in Breymann et al. (2003) and Reboredo (2011, 2012, 2013).

3.2. Downside and upside risk spillovers

We quantify downside and upside risk using downside and upside VaR for currency and stock returns, given that VaR quantifies the maximum loss that an investor may incur within a specific time horizon and confidence level by holding a long position (downside risk) or a short position (upside risk). Hence, both risk measures are relevant for safety-first investors who want to minimize the likelihood of extreme losses that may drive them out of business. They are also essential in terms of pricing, as investors should be compensated for assuming potential extreme market losses (see Poon et al., 2004).

For downside risk, VaR at time t and for a confidence level $1-\alpha$ is given by $\Pr(r_t\leqslant \mathrm{VaR}_{\alpha,t})=\alpha$, which can be computed from marginal models as $\mathrm{VaR}_{\alpha,t}=\mu_t+t_{\upsilon,\eta}^{-1}(\alpha)\sigma_t$, where μ_t and σ_t are the conditional mean and standard deviation of stock returns, computed according to Eqs. (8), (9), and where $t_{\upsilon,\eta}^{-1}(\alpha)$ denotes the α-quantile of the skewed Student-t distribution in Eq. (10). Similarly, we can compute the upside VaR by considering $\Pr(r_t\geqslant \mathrm{VaR}_{1-\alpha,t})=\alpha$; thus, upside VaR is given by $\mathrm{VaR}_{1-\alpha,t}=\mu_t+t_{\upsilon,\eta}^{-1}(1-\alpha)\sigma_t$.

To analyze the spillover risk from stock prices to exchange rates and vice versa, we considered the impact of financial distress in one market (measured by its VaR) on the VaR of another market. Spillover risk is closely related to the propagation of failures from one market to another, as confirmed in the systemic risk literature (see e.g., Billio et al., 2012; Bisias et al., 2012). To quantify downside or upside spillover risk, we employed the CoVaR measure as proposed by Adrian and Brunnermeier (2011) and generalized by Girardi and Ergün (2013). Namely, the CoVaR for the stock market is the VaR for stock market returns conditional on the fact that exchange rates experience an extreme movement. Let r_t^s be the returns for stocks and r_t^e be the returns for exchange rates. The (downside) CoVaR for stock returns and confidence level $1-\beta$ can be formally defined as the β-quantile of the conditional distribution of r_t^s as:

$$\Pr(r_t^s\leqslant \mathrm{CoVaR}_{\beta,t}^s|r_t^e\leqslant \mathrm{VaR}_{\alpha,t}^e)=\beta, \tag{11}$$

where $\mathrm{VaR}_{\alpha,t}^e$ is the α-quantile of the exchange rate return distribution: $\Pr(r_t^e\leqslant \mathrm{VaR}_{\alpha,t}^e)=\alpha$ measures the maximum loss that exchange rate returns may experience for a confidence level $1-\alpha$ and a specific time horizon. Similarly, we can measure (upside) CoVaR for a given extreme upward movement in exchange rate returns as:

$$\Pr(r_t^s\geqslant \mathrm{CoVaR}_{\beta,t}^s|r_t^e\geqslant \mathrm{VaR}_{1-\alpha,t}^e)=\beta, \tag{12}$$

where $\mathrm{VaR}_{1-\alpha,t}^e$ now measures the maximum loss by considering a short position for a confidence level $1-\alpha$ and for a specific time horizon. On the other hand, we can measure the systemic impact of stock prices on exchange rates by considering the CoVaR for the exchange rate market instead of for the stock market, as in Eqs. (11) and (12).

CoVaR in Eqs. (11) and (12) can be represented in terms of copulas, since the conditional probabilities can be re-written, respectively, as (see Eqs. (3) and (4)):

$$C\left(F_{r_t^s}(\mathrm{CoVaR}_{\beta,t}^s),F_{r_t^e}(\mathrm{VaR}_{\alpha,t}^e)\right)=\alpha\beta, \tag{13}$$

$$1-F_{r_t^s}(\mathrm{CoVaR}_{\beta,t}^s)-F_{r_t^e}(\mathrm{VaR}_{1-\alpha,t}^e)+C\left(F_{r_t^s}(\mathrm{CoVaR}_{\beta,t}^s),F_{r_t^e}(\mathrm{VaR}_{1-\alpha,t}^e)\right)=\alpha\beta. \tag{14}$$

where $F_{r_t^s}$ and $F_{r_t^e}$ are the marginal distributions of the stock and exchange rate returns, respectively. We can thus compute the CoVaR following a two-step procedure (see Reboredo and Ugolini, 2015): first, given the significance levels for the VaR and CoVaR (α and β, respectively) and for specific forms of the copula function we can solve Eqs. (13) or (14) in order to obtain the value of $F_{r_t^s}(\mathrm{CoVaR}_{\beta,t}^s)$; then, in a second step, using the distribution function for stock market returns as given by the marginal model in Eqs. (8)–(10), we can compute the CoVaR as $F_{r_t^s}^{-1}(F_{r_t^s}(\mathrm{CoVaR}_{\beta,t}^s))$.

We tested for the significance of systemic risk by comparing the cumulative distribution for CoVaR ($\mathrm{CoVaR}_{\beta,t}^s$) and the VaR ($\mathrm{VaR}_{\beta,t}^s$) of the stock market (or exchange rate market) using the KS bootstrapping test as proposed by Abadie (2002) and applied by Bernal et al. (2014) to compare CoVaR values. The KS test measures the difference between two cumulative quantile functions relying on the empirical distribution function but without considering any underlying distribution function. It is defined as:

$$\mathrm{KS}_{mn}=\left(\frac{mn}{m+n}\right)^{\frac{1}{2}}\sup_x|F_m(x)-G_n(x)|, \tag{15}$$

where $F_m(x)$ and $G_n(x)$ are the cumulative CoVaR and VaR distribution functions, respectively, and n and m are the size of the two samples. With this statistic we tested the hypothesis of no systemic impact between stock and exchange rates markets as:

$$\text{Hypothesis}: \mathrm{H}_0: \mathrm{CoVaR}_{\beta,t}^s=\mathrm{VaR}_{\beta,t}^s.$$

4. Data

We empirically studied co-movement and spillover effects between stock and exchange rate markets for a set of emerging economies (Brazil, Chile, Colombia, India, Mexico, Russia, South Africa and Turkey[3]) with flexible exchange rates. Since these economies have been gradually reducing foreign exchange and

[3] Despite the fact that China is the largest of the emerging economies, it was not included in the analysis because its exchange rate system is pegged to the USD.

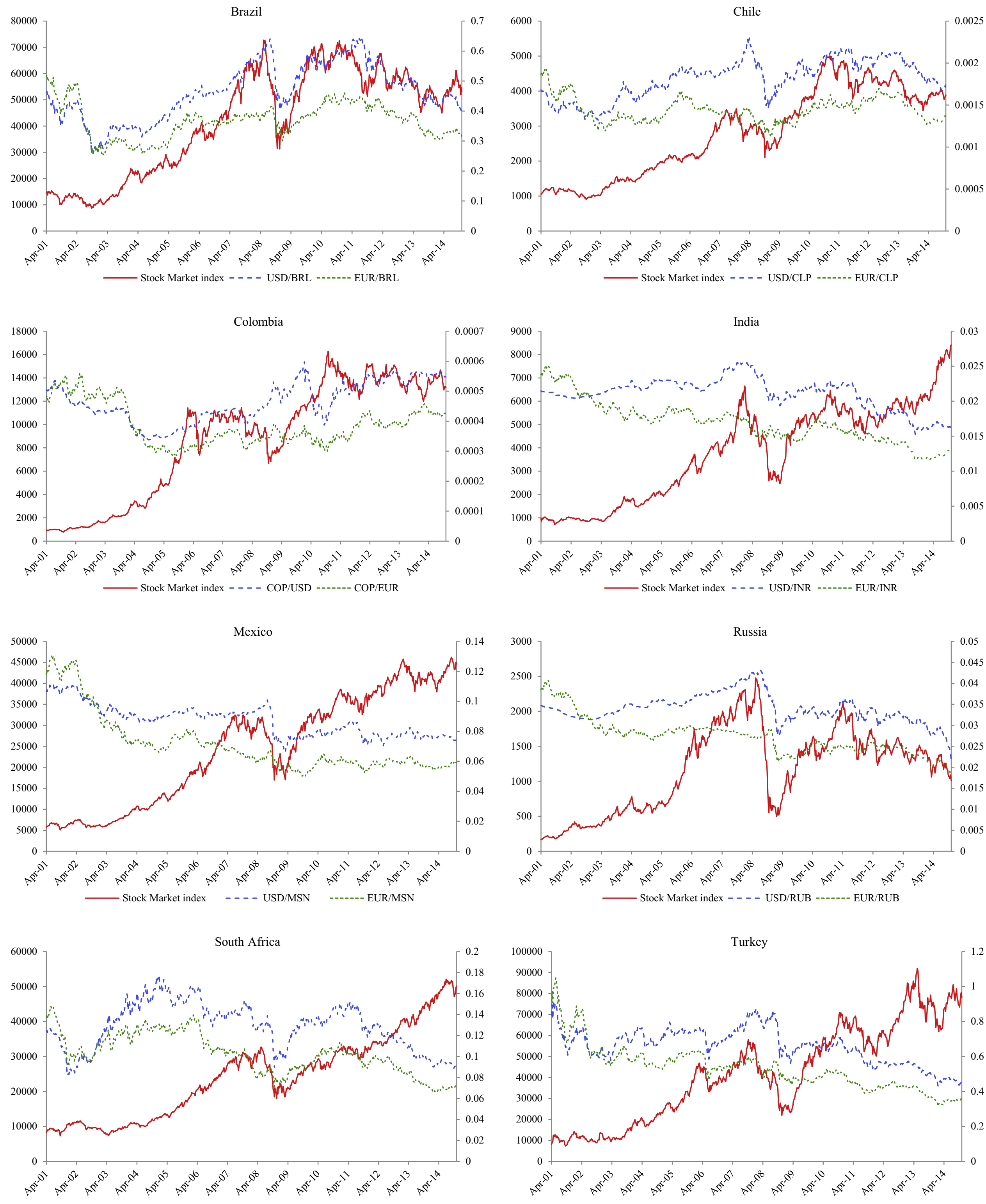

Fig. 1. Time series plots of weekly stock market indices and USD and EUR exchange rates in emerging markets for the period April 2001 to November 2014.

capital controls, they have been experiencing important inflows and outflows of capital and their stocks are becoming more relevant in international investor portfolios. The links between stock and exchange rate markets in those countries therefore require special consideration in terms of overall portfolio and risk management.

For each country we considered weekly data for the stock market index[4] and for the foreign currency exchange rate against the

[4] The stock market indices used for Brazil, Chile, Colombia, India, Mexico, Russia, South Africa and Turkey were Bovespa, IPSA, IGBC, BombaySE, IPC, RTSI, FTSE/JSE and ISE100, respectively.

Table 2
Descriptive statistics.

	Brazil	Chile	Colombia	India	Mexico	Russia	South Africa	Turkey
Panel A. Stock markets indices								
Mean	0.002	0.002	0.004	0.003	0.003	0.003	0.003	0.003
Std. Dev.	0.039	0.025	0.030	0.034	0.029	0.049	0.027	0.045
Maximum	0.168	0.147	0.094	0.152	0.186	0.342	0.160	0.258
Minimum	−0.223	−0.216	−0.205	−0.185	−0.179	−0.311	−0.103	−0.193
Skewness	−0.586	−1.037	−1.168	−0.517	−0.296	−0.543	−0.101	0.032
Kurtosis	6.440	13.348	10.890	6.392	8.839	10.131	6.578	6.832
J–B	390.2*	3290.6*	2000.5*	371.4*	1017.6*	1536.9*	379.5*	433.9*
Q(20)	32.269	26.003	36.478	47.470	32.253	55.302	35.872	16.591
	[0.041]	[0.206]	[0.014]	[0.001]	[0.041]	[0.000]	[0.016]	[0.679]
ARCH	5.713	7.187	3.239	6.237	11.108	14.311	11.598	3.561
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Panel B. USD exchange rate against the local currency								
Mean	0.000	0.000	0.000	0.000	−0.001	−0.001	0.000	−0.001
Std. Dev.	0.022	0.016	0.015	0.009	0.014	0.013	0.024	0.021
Maximum	0.087	0.063	0.084	0.052	0.056	0.045	0.134	0.101
Minimum	−0.130	−0.114	−0.126	−0.042	−0.146	−0.108	−0.112	−0.121
Skewness	−0.818	−1.017	−0.915	−0.149	−1.497	−1.755	−0.404	−0.482
Kurtosis	7.535	9.553	12.297	6.881	19.852	16.437	6.159	7.189
J-B	686.6*	1390.8*	2652.5*	447.7*	8654.2*	5697.6*	314.1*	545.9*
Q(20)	44.294	39.198	34.021	35.045	26.677	60.702	23.651	35.011
	[0.001]	[0.006]	[0.026]	[0.020]	[0.145]	[0.000]	[0.258]	[0.020]
ARCH	15.143	8.886	7.599	4.279	1.326	9.662	5.593	9.850
	[0.000]	[0.000]	[0.000]	[0.000]	[0.154]	[0.000]	[0.000]	[0.000]
Corr. S-E	0.65	0.33	0.27	0.48	0.48	0.49	0.16	0.60
Panel C. EUR exchange rate against the local currency								
Mean	−0.001	0.000	0.000	−0.001	−0.001	−0.001	−0.001	−0.001
Std. Dev.	0.023	0.018	0.017	0.014	0.017	0.013	0.022	0.021
Maximum	0.087	0.073	0.066	0.053	0.055	0.045	0.119	0.090
Minimum	−0.115	−0.088	−0.065	−0.053	−0.133	−0.094	−0.106	−0.089
Skewness	−0.487	−0.111	−0.013	0.193	−0.692	−0.985	−0.335	−0.223
Kurtosis	5.643	5.235	4.433	3.301	8.260	9.300	5.536	6.180
J-B	234.4*	149.1*	60.7*	7.1*	873.9*	1287.2*	203.2*	304.5*
Q(20)	42.583	16.857	31.548	31.099	21.955	43.399	30.187	54.500
	[0.002]	[0.662]	[0.048]	[0.054]	[0.343]	[0.002]	[0.067]	[0.000]
ARCH	12.085	5.754	5.389	2.677	1.033	6.939	2.531	6.276
	[0.000]	[0.000]	[0.000]	[0.000]	[0.420]	[0.000]	[0.000]	[0.000]
Corr. S-E	0.47	0.17	−0.06	0.13	0.21	0.18	0.03	0.53

Notes: Weekly data cover the period 13 April 2001 to 7 November 2014. J–B denote the Jarque–Bera statistics for normality. An asterisk (∗) indicates rejection of the null hypothesis at 5%. Q(20) is the Ljung–Box statistics for serial correlation in returns computed with 20 lags and ARCH denotes Engle's LM test for heteroskedasticity computed using 20 lags; *p* values for these tests are reported in squared brackets. Corr. S-E denotes the Pearson coefficient of correlation between stock and currency returns.

local currency. As foreign currencies we used the USD and the EUR, given that these are employed in most commercial and financial transactions in these emerging economies. Thus, an increase (decrease) in the exchange rate means an appreciation (depreciation) in the emerging economy's currency. Data, sourced from Datastream, covered the period 13 April 2001 to 7 November 2014.[5]

Fig. 1 shows temporal dynamics for each emerging economy for the stock market indices and for the USD and EUR exchange rates against the local currency. A superficial inspection of the data shows that the intensity of co-movement between stock and currency markets varied across time and countries, even though local currency appreciation was linked to increases in local stock market values, consistent with the theory predictions. Price volatility in stock and exchange rate markets also changed over the sample period, mainly around the time of the onset of the global financial crisis, although to significantly different degrees across countries—a fact which may have implications for temporal dependence between stock prices and exchange rates.

Panel A in Table 2 reports descriptive statistics for stock price returns for all the emerging economies considered. Average returns were close to zero, whereas differences in standard deviations indicate dispersion in volatility behavior across markets. Likewise, large differences between maximum and minimum price returns show that price ranges were greater for the Russian and Turkish stock markets than for the other stock markets. Negative skewness values were common to all the stock markets except Turkey, and the return series showed high values for the kurtosis statistic, consistent with fat tails in the return distributions. As a result, stock return normality was rejected by the Jarque–Bera statistics. Moreover, the Ljung–Box statistic suggests the presence of serial correlation in most of the countries, while the autoregressive conditional heteroskedasticity-Lagrange multiplier (ARCH-LM) statistic indicated that ARCH effects could be found in all the return series.

Panels B and C in Table 2 report descriptive statistics for USD and EUR exchange rate returns, respectively, against the local currencies. Average returns were close to zero and standard deviations show that volatility was similar for the USD and the EUR exchange rates. However, skewness and kurtosis values indicate that the USD exchange rates were more left skewed and displayed heavier tails than the EUR exchange rates. For the return series for both currencies, normality was rejected; furthermore, the Ljung–Box statistic suggested the presence of serial correlation for most of series, while the ARCH-LM statistic indicated that ARCH effects were present in all the exchange rate return series (except for Mexico). The Pearson coefficient reflecting correlation between stock and

[5] The start of the sample period was determined by the stabilization of large swings in the Turkish stock market that emerged as a result of the onset of the banking crisis at the end of 2000.

Table 3
Parameter estimates for marginal models of stock market returns.

	Brazil	Chile	Colombia	India	Mexico	Russia	South Africa	Turkey
Mean								
ϕ_0	0.00	0.00*	0.00*	0.00*	−0.06	0.00	0.00*	0.00*
	(0.86)	(2.41)	(2.38)	(2.84)	(−0.05)	(1.91)	(3.07)	(2.40)
ϕ_1	−0.79*		0.79*	−0.34*	0.68*	0.88*	0.38*	
	(−7.32)		(9.54)	(−4.86)	(4.23)	(5.13)	(2.10)	
θ_1	0.74*		−0.73*	0.42*	−0.72*	−0.85*	−0.45*	
	(6.45)		(−8.64)	(6.67)	(−4.55)	(−4.60)	(−2.45)	
ϕ_2				0.09*				
				(2.04)				
Variance								
ω	0.55*	0.74	0.72	0.79*	0.32	0.73*	0.29*	0.45
	(2.19)	(1.65)	(1.52)	(2.06)	(1.78)	(2.50)	(2.11)	(1.77)
α_1	0.00	0.03	0.11*	0.10*	0.01	0.10*	0.00	0.05*
	(−0.18)	(1.19)	(2.14)	(2.35)	(0.35)	(4.55)	(0.07)	(2.57)
β_1	0.90*	0.73*	0.83*	0.74*	0.85*	0.86*	0.86*	0.92*
	(36.84)	(5.80)	(9.94)	(10.25)	(14.94)	(30.513)	(23.14)	(32.08)
λ	0.11*	0.18*			0.06*		0.17*	
	(2.94)	(1.99)			(2.40)		(2.84)	
Asymmetry	−0.29*	−0.13*	−0.06	−0.18*	−0.19*	−0.17*	−0.27*	−0.12*
	(−4.74)	(−2.21)	(−1.24)	(−2.86)	(−2.77)	(−2.64)	(−4.98)	(−2.52)
Tail	22.02*	7.88*	3.39*	9.48*	36.98	9.78*	12.63*	6.69*
	(2.41)	(3.75)	(6.61)	(2.89)	(1.01)	(3.08)	(2.46)	(3.91)
LogLik	1376.65	1712.36	1584.09	1506.01	1690.91	1279.35	1662.36	1259.358
LJ	16.38	17.36	20.08	24.04	24.45	17.98	22.02	16.26
	[0.57]	[0.50]	[0.33]	[0.11]	[0.08]	[0.45]	[0.23]	[0.70]
LJ 2	10.85	15.34	11.87	14.23	22.51	12.49	10.88	9.61
	[0.90]	[0.64]	[0.85]	[0.71]	[0.21]	[0.82]	[0.90]	[0.94]
ARCH	0.47	0.74	0.53	0.73	0.89	0.58	0.51	0.58
	[0.98]	[0.79]	[0.95]	[0.78]	[0.60]	[0.91]	[0.96]	[0.93]
KS	[0.65]	[0.71]	[0.98]	[0.81]	[0.59]	[0.89]	[0.97]	[0.86]
CvM	[0.85]	[0.89]	[0.98]	[0.92]	[0.86]	[0.92]	[0.99]	[0.90]
AD	[0.79]	[0.95]	[0.99]	[0.98]	[0.92]	[0.97]	[0.99]	[0.92]

Notes: The table presents parameter estimates and z statistics (in parentheses) for the marginal models described in Eqs. (8)–(10). LogLik is the log-likelihood value; LJ denotes the Ljung–Box statistics for serial correlation in the residual model calculated with 20 lags, while LJ 2 is the Ljung–Box statistics for serial correlation in the squared residual model calculated with 20 lags. ARCH is Engle's LM test for the ARCH effect in residuals up to 20th order. KS, CvM and AD denote the Kolmogorov–Smirnov, Cramér–von Mises and Anderson–Darling tests for adequacy of the skewed-t distribution model. P values (in square brackets) below 0.05 indicate rejection of the null hypothesis. An asterisk ($*$) indicates significance at 5%.

Table 4
Parameter estimates for marginal models of the USD exchange rate against the local currency.

	Brazil	Chile	Colombia	India	Mexico	Russia	South Africa	Turkey
Mean								
ϕ_0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.23)	(1.09)	(1.41)	(−0.73)	(−0.17)	(−1.23)	(−0.59)
ϕ_1				0.82*		0.94*		
				(9.55)		(24.28)		
θ_1				−0.74*		−0.88*		
				(−7.61)		(−14.21)		
Variance								
ω	0.22*	0.09	0.01	0.18	0.05*	0.00	0.16	0.21
	(2.71)	(1.43)	(1.31)	(0.87)	(2.47)	(0.66)	(1.89)	(1.64)
α_1	0.07	0.11*	0.19*	0.45*	0.03	0.28*	0.08*	0.19*
	(1.93)	(2.73)	(4.32)	(2.01)	(1.14)	(4.22)	(2.78)	(3.56)
β_1	0.81*	0.85*	0.84*	0.80*	0.87*	0.81*	0.90*	0.77*
	(19.53)	(15.32)	(27.19)	(22.35)	(29.66)	(22.69)	(26.50)	(10.96)
λ	0.14*				0.14*			
	(3.01)				(3.18)			
Asymmetry	−0.21*	−0.11*	−0.13*	−0.04	−0.16*	0.03	−0.20*	−0.21*
	(−4.17)	(−2.13)	(−2.74)	(−0.67)	(−2.85)	(0.57)	(−3.53)	(−3.99)
Tail	10.54*	6.58*	4.77*	2.62*	11.86*	4.30*	9.13*	7.14*
	(2.72)	(4.12)	(4.94)	(4.79)	(2.67)	(4.76)	(3.32)	(4.14)
LogLik	1813.78	2024.06	2151.35	2555.51	2163.58	2472.66	1697.59	1842.92
LJ	28.49	19.27	27.60	24.38	23.44	19.06	17.99	26.81
	[0.10]	[0.50]	[0.12]	[0.14]	[0.27]	[0.39]	[0.59]	[0.14]
LJ 2	17.49	7.19	8.44	12.87	12.50	11.28	14.68	15.92
	[0.49]	[0.99]	[0.97]	[0.80]	[0.82]	[0.88]	[0.68]	[0.59]
ARCH	0.84	0.46	0.42	0.73	0.58	0.562	0.65	0.80
	[0.67]	[0.91]	[0.94]	[0.80]	[0.93]	[0.90]	[0.98]	[0.71]
K–S	[0.91]	[0.99]	[0.47]	[0.68]	[0.98]	[0.82]	[0.97]	[0.92]
C–vM	[0.84]	[0.98]	[0.68]	[0.41]	[0.99]	[0.89]	[0.95]	[0.83]
A–D	[0.91]	[0.99]	[0.81]	[0.40]	[1.00]	[0.91]	[0.96]	[0.86]

Notes: See notes for Table 3.

Table 5
Parameter estimates for marginal models of the EUR exchange rate against the local currency.

	Brazil	Chile	Colombia	India	Mexico	Russia	South Africa	Turkey
Mean								
ϕ_0	0.00	0.00	0.00	0.00	0.00	0.00*	0.00	0.00
	(−0.64)	(−0.87)	(−0.72)	(−1.22)	(−0.97)	(−1.99)	(−1.32)	(−1.57)
ϕ_1	−0.80*		0.09*			−0.08*		0.80*
	(−9.59)		(2.36)			(−2.18)		(12.49)
θ_1	0.74*							−0.74*
	(7.96)							(−11.95)
Variance								
ω	0.22*	0.07	0.02	0.05	0.11	0.02	0.23	0.13
	(2.76)	(1.39)	(1.26)	(1.54)	(1.10)	(0.85)	(1.25)	(1.58)
α_1	0.06*	0.06*	0.05*	0.05*	0.06	0.14*	0.06*	0.02
	(1.98)	(2.85)	(2.88)	(2.83)	(1.77)	(2.08)	(2.15)	(0.41)
β_1	0.84*	0.91*	0.94*	0.92*	0.89*	0.87*	0.88*	0.36*
	(24.92)	(29.04)	(41.91)	(33.09)	(12.83)	(13.04)	(13.70)	(3.03)
λ	0.09*							0.14*
	(2.19)							(3.08)
Asymmetry	−0.13*	0.00	−0.08	0.13*	−0.04	−0.08	−0.21*	−0.15*
	(−2.75)	(−0.03)	(−1.38)	(1.99)	(−0.76)	(−1.46)	(−3.93)	(−2.78)
Tail	11.04*	9.92*	14.18*	99.99*	9.18*	5.97*	6.52*	14.48*
	(2.72)	(3.24)	(2.26)	(28.61)	(2.46)	(5.07)	(4.68)	(2.20)
LogLik	1763.11	1905.83	1954.43	2062.84	1930.39	2169.46	1744.57	1906.21
LJ	21.01	7.43	24.22	19.81	22.18	23.44	18.99	22.24
	[0.28]	[0.99]	[0.19]	[0.47]	[0.33]	[0.22]	[0.52]	[0.05]
LJ 2	17.72	24.01	17.66	18.32	3.86	12.48	17.78	20.52
	[0.47]	[0.16]	[0.48]	[0.43]	[0.99]	[0.82]	[0.47]	[0.25]
ARCH	0.77	1.08	0.89	0.96	0.18	0.67	0.86	1.02
	[0.75]	[0.36]	[0.60]	[0.50]	[0.99]	[0.85]	[0.64]	[0.44]
K–S	[0.95]	[0.96]	[0.95]	[0.87]	[0.72]	[0.78]	[0.79]	[0.99]
C–vM	[0.98]	[0.94]	[0.98]	[0.74]	[0.85]	[0.77]	[0.97]	[0.98]
A–D	[0.99]	[0.98]	[0.99]	[0.81]	[0.91]	[0.81]	[0.98]	[0.99]

Notes: See notes for Table 3.

exchange rate returns indicates a positive relationship between equity and currency returns, with the exception of the EUR for Colombia. Correlation values varied across countries and across currencies, taking larger values for the USD than for the EUR—consistent with the relative importance of the USD in financial and commercial transactions in these emerging economies.

5. Results

5.1. Marginal model results

The marginal models in Eqs. (8)–(10) were estimated for stock market returns for the different countries and for the USD and EUR exchange rates against local currencies. The values of the p, q, r and m parameters were chosen—considering lag values ranging from zero to a maximum of two—so as to minimize the AIC values. Table 3 reports results for the stock market returns: average returns displayed serial correlation in most of the countries, volatility was persistent across markets and asymmetric volatility effects were evident in half of the stock market index returns. Estimates of the asymmetry and degrees of freedom parameters for the skewed Student-*t* distribution indicated that error terms are well characterized by a distribution with asymmetries and fat tails. The last rows of Table 3 provide information on different goodness-of-fit tests, indicating that serial correlation and ARCH effects were adequately reflected by the marginal models. We also tested the adequacy of the skewed-*t* distribution by testing the null hypothesis that the standardized model residuals were uniform (0,1), comparing the empirical and theoretical distributions of the standardized residuals using the KS, Cramér–von Mises (CvM) and Anderson–Darling (AD) tests. According to the *p* values for these tests, the null of correct specification of the distribution model could not be rejected at the 5% significance level. Hence, our tests indicate that there is no mis-specification problems in our marginal models for stock returns.

Tables 4 and 5 report marginal model estimates for the local currency against the USD and the EUR, respectively. Average exchange returns displayed, in general, no serial correlation, whereas volatility estimates confirm volatility to have been persistent across countries for the two foreign exchange rates. Leverage effects were hardly observed outside of Brazil and Turkey for the EUR and outside Brazil and Mexico for the USD. Asymmetry parameter estimates for the distribution indicated that this feature was more relevant for the USD than for the EUR. Likewise, estimates for the degrees of freedom confirmed that the error terms were not normal and had fat tails. The goodness-of-fit test indicated that neither autocorrelation nor ARCH effects remained in the residuals. Furthermore, the results for the KS, CvM and AD tests for the adequacy of the skewed-*t* distribution provided no evidence against correct specification of the distribution model at the 5% significant level. Consequently, our marginal models for exchange rates were not mis-specified.

5.2. Copula model results

We estimated static and time-varying versions of the bivariate copula models reported in Table 1 for stock market returns and USD rate pairs and for stock market returns and EUR rate pairs. We used as observations the probability integral transformation of the standardized residuals from the marginal models reported in Tables 3–5, selecting the best copula model as the one that yielded the best AIC value corrected for small-sample bias.

Table 6 reports estimates for the stock market returns and USD rate pairs. The empirical evidence indicates that there was positive and significant dependence between stock and USD exchange rate returns for all countries; hence, those variables co-moved in a way

Table 6
Bivariate copula model estimates for stock market and USD exchange rate returns.

Copula	Brazil	Chile	Colombia	India	Mexico	Russia	South Africa	Turkey
Panel A. Time-invariant copulas								
Gaussian								
ρ	0.590*	0.211*	0.230*	0.286*	0.346*	0.460*	0.079*	0.574*
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)
AIC	−300.585	−30.333	−36.556	−58.538	−88.696	−166.625	−2.424	−281.497
Student-*t* copula								
ρ	0.594*	0.216*	0.244*	0.301*	0.347*	0.465*	0.082*	0.574*
	(0.02)	(0.03)	(0.04)	(0.05)	(0.03)	(0.03)	(0.04)	(0.03)
υ	11.793*	6.346*	8.005*	7.693	28.066*	7.405*	4.934*	7.014*
	(4.87)	(1.10)	(3.75)	(7.82)	(13.04)	(2.26)	(1.09)	(2.77)
AIC	−306.003	−43.425	−43.285	−68.180	−87.679	−177.790	−25.274	−297.372
Gumbel								
δ	1.598*	1.131*	1.151*	1.199*	1.248*	1.397*	1.053*	1.554*
	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)	(0.05)
AIC	−271.453	−21.700	−25.860	−44.344	−75.815	−148.765	−3.923	−247.053
Rotated Gumbel								
δ	1.604*	1.170*	1.179*	1.231*	1.248*	1.414*	1.076*	1.603*
	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.05)
AIC	−281.838	−51.503	−48.985	−72.395	−75.642	−172.978	−9.358	−295.018
BB7								
θ	1.453*	1.025*	1.028*	1.052*	1.180*	1.256*	1.023*	1.314*
	(0.07)	(0.04)	(0.05)	(0.04)	(0.05)	(0.06)	(0.03)	(0.08)
δ	0.679*	0.303*	0.296*	0.399*	0.303*	0.558*	0.137*	0.812*
	(0.08)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.05)	(0.08)
AIC	−288.076	−44.471	−41.464	−72.052	−81.546	−178.042	−10.109	−293.656
Panel B. Time-varying copulas								
TVP-Gaussian								
ψ_0	0.643	0.709*	0.762*	0.017	1.312	1.653*	0.000	2.069*
	(0.87)	(0.15)	(0.16)	(0.01)	(9.48)	(0.51)	(0.00)	(0.47)
ψ_1	0.274	0.532*	0.565*	0.117*	0.313	0.755*	0.092*	−0.215*
	(0.16)	(0.15)	(0.19)	(0.04)	(0.93)	(0.15)	(0.02)	(0.10)
ψ_2	0.950	−1.984*	−1.552*	1.944*	−2.000	−2.000*	2.015*	−1.151
	(1.60)	(0.11)	(0.37)	(0.07)	(29.90)	(1.01)	(0.02)	(0.82)
AIC	−304.725	−40.666	−41.126	−79.855	−87.511	−182.910	−80.429	−283.696
TVP-Student								
ψ_0	2.755*	0.819*	0.846*	0.012	1.281*	1.769*	−0.001	2.313*
	(0.26)	(0.16)	(0.18)	(0.01)	(0.16)	(0.41)	(0.00)	(0.75)
ψ_1	0.164*	0.172*	0.242*	0.077*	0.288*	0.317*	0.068*	−0.033
	(0.08)	(0.08)	(0.12)	(0.03)	(0.12)	(0.09)	(0.02)	(0.05)
ψ_2	−2.487*	−2.049*	−1.622*	1.978*	−1.901*	−1.927*	2.019*	−1.728
	(0.33)	(0.08)	(0.39)	(0.06)	(0.23)	(0.78)	(0.02)	(1.31)
υ	13.780*	7.387*	9.086*	10.772	34.741	8.759*	7.708*	7.117*
	(1.33)	(2.38)	(3.73)	(6.15)	(18.40)	(2.62)	(2.54)	(2.05)
AIC	**−306.378**	−49.694	−44.803	**−81.973**	**−89.043**	−187.385	**−90.825**	−293.631
TVP-Gumbel								
ω	1.822*	0.774	1.776*	−0.302*	1.590*	1.470*	−0.198	1.287*
	(0.18)	(0.51)	(0.20)	(0.08)	(0.27)	(0.26)	(0.12)	(0.53)
β	−0.550*	−0.119	−0.979*	0.725*	−0.710*	−0.335*	0.674*	−0.253
	(0.13)	(0.40)	(0.19)	(0.04)	(0.24)	(0.16)	(0.07)	(0.34)
α	−0.767	−1.053	−0.911*	−0.488*	−0.750*	−1.524*	−0.886*	−0.669*
	(0.39)	(0.60)	(0.37)	(0.20)	(0.37)	(0.43)	(0.18)	(0.30)
AIC	−273.779	−23.456	−28.529	−54.997	−76.592	−161.591	−35.674	−247.266
TVP-Rotated Gumbel								
ω	1.877*	−0.084	1.645*	−0.344*	1.684*	1.441*	−0.100	0.931
	(0.07)	(0.51)	(0.28)	(0.11)	(0.15)	(0.28)	(0.12)	(0.80)
β	−0.600*	0.527	−0.773*	0.741*	−0.845*	−0.316	0.616*	−0.084
	(0.04)	(0.39)	(0.21)	(0.07)	(0.15)	(0.17)	(0.06)	(0.51)
α	−0.579*	−0.451*	−1.012*	−0.364*	−0.466	−1.420*	−0.912*	−0.109
	(0.24)	(0.19)	(0.46)	(0.16)	(0.32)	(0.50)	(0.19)	(0.31)
AIC	−284.346	**−52.586**	**−55.550**	−79.656	−74.666	−184.119	−43.748	−291.123
TVP-BB7								
ω_θ	0.562	1.003*	1.457	−0.048	1.235*	1.905*	−0.646*	1.659*
	(1.98)	(0.44)	(2.36)	(0.57)	(0.37)	(0.11)	(0.13)	(0.29)
β_θ	−0.769	−0.365	0.540	−1.789*	−1.456*	−0.659*	−0.760*	−3.065*
	(4.47)	(0.49)	(0.91)	(0.70)	(0.28)	(0.32)	(0.31)	(1.54)
α_θ	−0.668*	−1.023	−1.668	0.596	−0.335	−0.991*	0.987*	−0.452*
	(0.09)	(0.57)	(2.12)	(0.41)	(0.30)	(0.13)	(0.08)	(0.17)
ω_δ	−0.163	0.619*	1.109*	0.515*	0.212	1.405*	0.638*	0.476*
	(3.77)	(0.19)	(0.18)	(0.08)	(0.14)	(0.15)	(0.06)	(0.06)

Table 6 (*continued*)

Copula	Brazil	Chile	Colombia	India	Mexico	Russia	South Africa	Turkey
β_δ	−0.275	−0.706	−1.290*	−0.473	0.502	−2.362*	−1.061*	−0.014
	(6.88)	(0.40)	(0.46)	(0.25)	(0.40)	(0.66)	(0.22)	(0.43)
α_δ	−0.370	0.373	−0.483	0.571*	0.609*	−0.200	0.489*	0.528*
	(4.01)	(0.35)	(0.36)	(0.06)	(0.11)	(0.11)	(0.04)	(0.01)
AIC	−97.698	−43.717	−44.835	−75.696	−80.876	**−189.667**	−42.564	**−301.752**

Notes: The table reports estimates and standard errors (in brackets) for the different copula models for stock market and USD exchange rate returns for different emerging economies. 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. For the time-varying parameter (TVP) copulas, q in Eqs. (5)–(7) was set to 10. An asterisk (*) indicates significance of the parameter at 5%.

that increased (decreased) stock prices were associated with local currency appreciation (depreciation) with respect to the USD—consistent with the linear correlation evidence reported in Table 2 and with the idea that an increase (decrease) in local stock market prices attracts (discourages) capital inflows, thereby appreciating (depreciating) the local currency. This evidence corroborates the results reported by Cho et al. (2016). Comparing different copula specifications, the AIC values support time-varying copulas as the best specifications for all pairs. Time-varying symmetric tail dependence given by the Student-*t* copula was observed for Brazil, India, Mexico and South Africa; asymmetric tail dependence with lower tail dependence and no upper tail dependence, as given by the rotated Gumbel copula, were found for Chile and Colombia, whereas asymmetric tail dependence, as given by the BB7 copula, was found for Russia and Turkey. Thus, our copula results point to the existence of lower tail dependence in all the countries. Hence, extreme downward movements in stock prices were accompanied by local currency depreciations in emerging markets. This result is consistent with capital outflows induced by flight-to-quality (see also Cho et al., 2016). The dynamics of dependence over the sample period is represented in Panel A in Fig. 2, where we can view how copula dependence parameters changed, with big swings in India and South Africa having implications for spillovers that we discuss below.

Table 7 reports the static and time-varying copula estimates for stock market returns and the EUR exchange rate. As for the USD rate, we found evidence of positive and significant dependence between stock and EUR exchange returns for all the countries, with the exception of Colombia and India, where Gaussian copula correlation was small and insignificant. Thus, the EUR co-moved with stock prices against local currencies for most of the countries, i.e., local currency appreciation (depreciation) against the EUR moved in the same direction as stock price increases (decreases). In the case of Colombia and India, stock market co-movement with the USD and the absence of co-movement with the EUR is consistent with the relative importance of the USD for those countries and the minor role played by the EUR. According to the AIC values, time-varying copulas offered better fits for Brazil, Russia, South Africa and Turkey, whereas static copulas offered better fits for Chile, Colombia, India and Mexico. In contrast to evidence for the USD, we found evidence of tail independence for Colombia, India, Mexico and Russia, and of upper tail independence and lower tail dependence for Chile (as given by the static rotated Gumbel copula). Evidence of symmetric tail dependence—given by the TVP Student-*t* copula—was observed for Brazil and South Africa, whereas Turkey exhibited asymmetric tail dependence given by the TVP BB7 copula. These results show that extreme market movements in stock and exchange rate markets against the EUR were imperfectly coupled, so information transmission and integration between those markets greatly differed from the dependence observed for stock markets and the USD. This different behavior has implications for systemic risk as we will see below. Panel B in Fig. 2, depicting the dynamics of the copula parameter estimates, shows that dependence fluctuated in four out of eight countries, but mainly in Russia and in South Africa, where correlations moved along the sample from positive to negative values and from negative to positive values.

5.3. Exchange rate spillover effects to stock returns

Using the best copula fit and following the two-step procedures described above, for each time period we obtained the CoVaR value for stock returns at the 95% confidence level ($\beta = 0.05$) conditional on the VaR value for the exchange rate returns at the 95% confidence level ($\alpha = 0.05$).[6] Considering spillover effects from exchange rates to stock returns, Fig. 3 shows the temporal dynamics of results for the downside and upside VaR and CoVaR values for stock returns, whereas Table 8 reports summary statistics and hypothesis test results.

Panel A in Fig. 3 reflects downside and upside VaR and CoVaR dynamics, considering the USD rate, for stock returns in different countries. The graphical evidence indicates that VaR and CoVaR values followed the same trend in all countries, although there were differences in magnitude across countries, with the impact of the global financial crisis reflected by abrupt changes. Considering downside risk, consistently with the lower tail dependence observed for the copulas between USD rates and stock returns, we observed that CoVaR values were systematically below the VaR values in all the countries. This graphical evidence is corroborated by the results of the KS bootstrapping test (see Eq. (15)) reported in Panel A in Table 8. Thus, extreme downwards movements in exchange rates (depreciation of the local currency against the USD) had a spillover effect on stock markets—to the extent that their VaR fell significantly as a result of an extreme drop in exchange rates. This evidence is consistent with co-movements in the lower stock and exchange rate return tails; it is also consistent with the fact that (extreme) depreciation of a local currency may trigger flight-to-quality of foreign investors, with capital moving out of emerging economies and their stock prices falling. Investors in emerging markets need to bear this fact in mind so as to protect their portfolios against downside risk by taking into account both stock market and exchange rate downside risk, given that currency does not provide any hedge for investments in emerging markets. Thus, for these investors, hedging downside risk spillovers from currency risk implies taking short exchange rate positions.

Considering upside risk, we found that CoVaR values were greater than VaR values; however, there were differences across countries, some of which exhibited upper tail dependence. Thus, for Colombia and Chile, we observed that there was little difference between CoVaR and VaR values, even though these were reported as significant by the KS statistic results reflected in Panel A in

[6] Results at the 99% confidence level, which were consistent with the results reported here, are available on request.

Panel A. USD exchange rate and stock market returns.

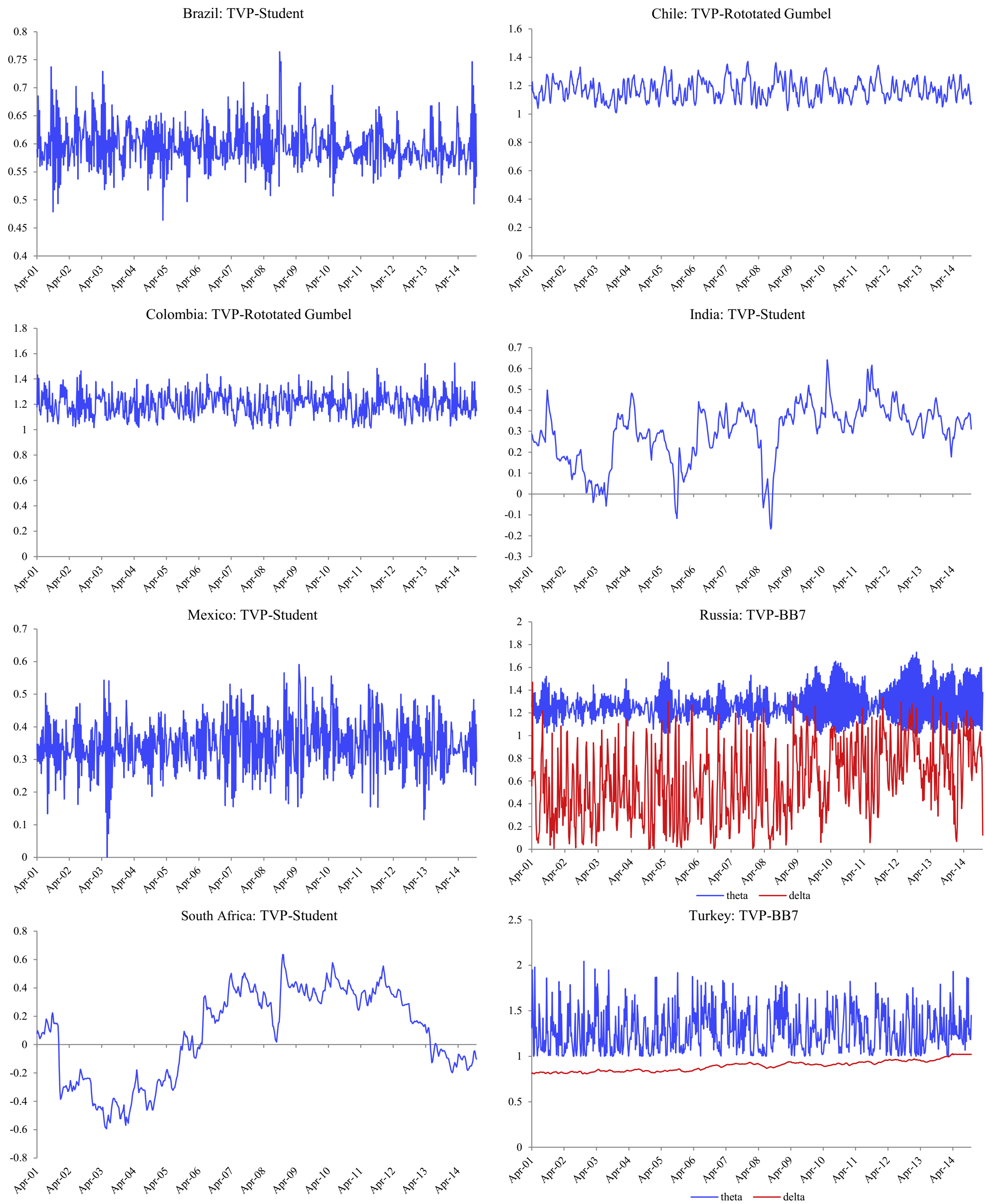

Fig. 2. Time series plots for parameter estimates of the best copula fit between stock and currency returns.

Table 8; thus, extreme appreciation in the currencies of emerging markets have an impact on the upside risk of their stock returns, even though the magnitude of this impact is less than for downside risk. In contrast, for the stock markets in the remaining countries, we found clear evidence of upside risk spillover effects from the USD exchange rate, given that the upside CoVaR values were significantly greater than the upside VaR values—corroborated by the results of the KS test reported in Panel A in Table 8. The economic interpretation of this result is similar to that for the downside risk, but considering short instead of long positions.

Panel B. EUR exchange rate and stock market returns.

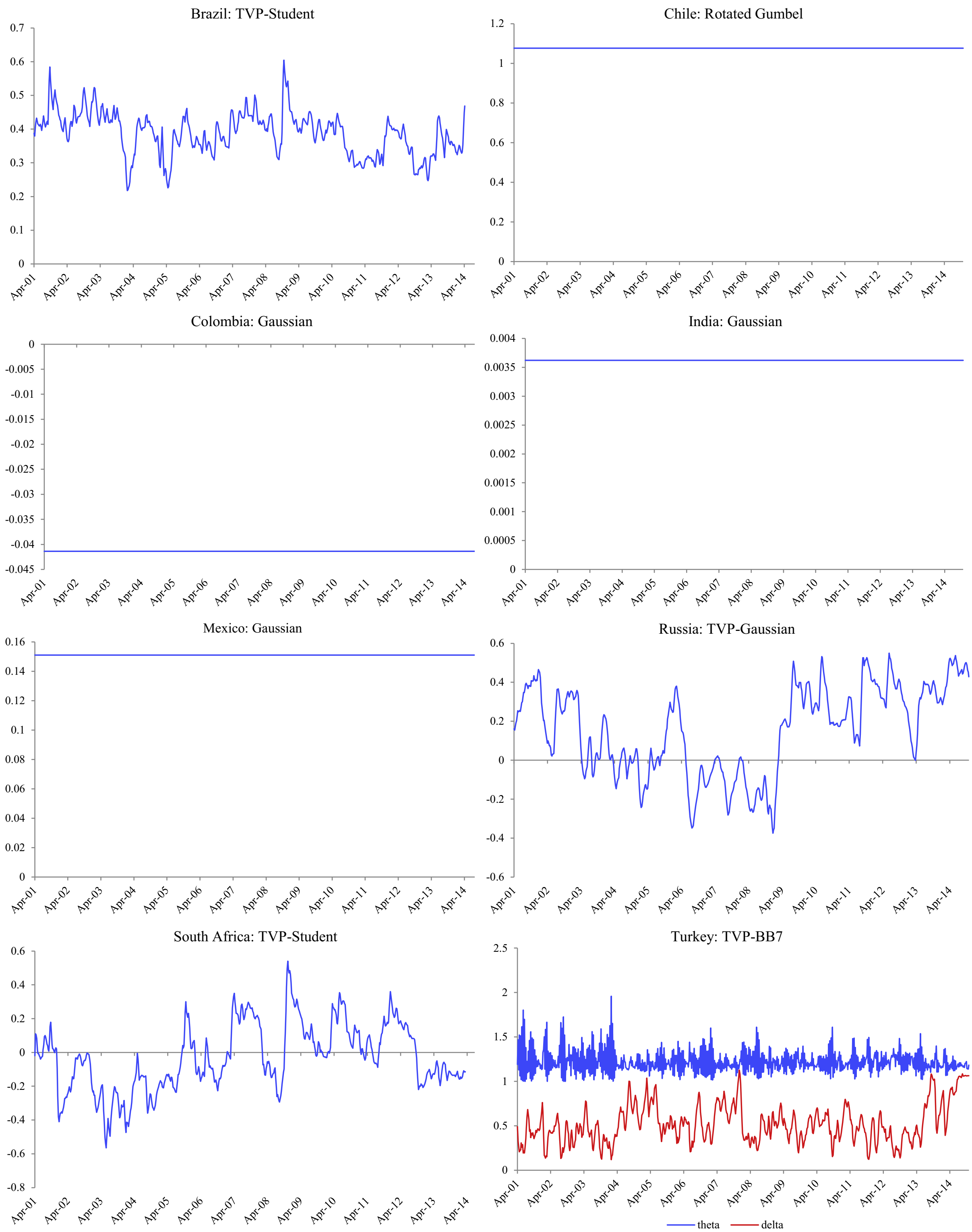

Fig. 2 (*continued*)

Regarding the downside and upside risk spillovers from the EUR to emerging stock markets, Panel B in Fig. 3 reflects downside and upside VaR and CoVaR dynamics for stock returns in the different countries. As happened with the USD, VaR and CoVaR values followed the same trend in all the countries, although they differed in magnitude. Downside (upside) CoVaR values were, in general, higher (lower) for the EUR than for the USD; hence, the size of spillovers differed across currencies. Regarding downside risk, we observed spillover effects for all the countries except Colombia and India, where there was no downside spillover effects from

Table 7
Bivariate copula model estimates for stock market and EUR exchange rate returns.

Copula	Brazil	Chile	Colombia	India	Mexico	Russia	South Africa	Turkey
Panel A. Time-invariant copulas								
Gaussian								
ρ	0.387*	0.083*	−0.041	0.004	0.151*	0.161*	−0.020	0.425*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)	(0.02)
AIC	−113.276	−2.913	**0.793**	**1.996**	−**14.365**	−16.610	1.723	−139.033
Student-*t*								
ρ	0.390*	0.084*	−0.047	0.005	0.153*	0.160*	−0.027	0.427*
	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)
υ	10.822*	6.264*	18.386*	57.745*	31.370	11.243*	8.008*	9.705*
	(3.45)	(2.58)	(5.61)	(24.18)	(24.84)	(5.62)	(2.59)	(2.83)
AIC	−117.674	−16.685	0.829	3.853	−13.024	−18.868	−6.598	−146.365
Gumbel								
δ	1.308*	1.043*	1.000*	1.000*	1.091*	1.087*	1.006*	1.335*
	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.02)	(0.04)
AIC	−106.933	−1.101	2.006	2.006	−11.188	−8.878	1.844	−120.121
Rotated Gumbel								
δ	1.297*	1.077*	1.008*	1.003*	1.085*	1.116*	1.010*	1.360*
	(0.04)	(0.02)	(0.01)	(0.02)	(0.03)	(0.03)	(0.02)	(0.04)
AIC	−103.722	−**17.897**	1.136	1.988	−10.169	−25.344	1.652	−141.800
BB7								
θ	1.251*	1.001	1.001*	1.001*	1.071*	1.001	1.010*	1.190*
	(0.06)	(0.58)	(0.38)	(0.46)	(0.04)	(0.62)	(0.02)	(0.06)
δ	0.347*	0.145	0.001	0.006	0.095	0.221	0.012	0.491*
	(0.06)	(0.27)	(0.94)	(0.32)	(0.05)	(0.30)	(0.04)	(0.07)
AIC	−116.855	−9.961	4.056	4.034	−8.867	−23.155	3.604	−142.225
Panel B. Time-varying copulas								
TVP-Gaussian								
ψ_0	0.067	0.112	−0.101	0.012	0.399*	0.012	−0.005	1.225*
	(0.09)	(0.11)	(0.17)	(0.10)	(0.18)	(0.01)	(0.01)	(0.26)
ψ_1	0.130	0.435	0.133	0.039	0.267	0.130*	0.157*	0.372*
	(0.08)	(0.25)	(0.19)	(0.21)	(0.23)	(0.04)	(0.05)	(0.16)
ψ_2	1.835*	0.172	−0.594	−0.683	−0.903	1.922*	1.763*	−1.093*
	(0.29)	(1.19)	(3.26)	(1.72)	(0.98)	(0.07)	(0.12)	(0.48)
AIC	−118.018	−11.415	4.228	5.991	−11.782	−**50.031**	−25.114	−141.129
TVP-Student								
ψ_0	−0.007	0.293	−0.097	−0.204*	0.375*	0.316	−0.004	−0.038
	(0.17)	(0.16)	(0.11)	(0.01)	(0.14)	(0.22)	(0.01)	(0.07)
ψ_1	0.047	0.083	0.122	0.022*	0.328*	0.430	0.086*	0.025
	(0.15)	(0.05)	(0.12)	(0.00)	(0.16)	(0.23)	(0.04)	(0.02)
ψ_2	2.087*	−1.974*	−0.069	−2.036*	−0.860	−0.363	1.870*	2.207*
	(0.54)	(0.04)	(1.53)	(0.00)	(0.76)	(1.58)	(0.09)	(0.19)
υ	11.663	6.745*	19.346*	45.000	38.137	10.806*	10.000*	10.142*
	(70.95)	(1.84)	(2.60)	(25.80)	(78.93)	(4.69)	(3.40)	(4.19)
AIC	−**118.497**	−16.791	3.570	3.706	−12.882	−30.473	−**28.032**	−144.120
TVP-Gumbel								
ω	1.211	−1.088*	0.000	0.000	1.277	1.336*	−1.443*	0.209
	(1.15)	(0.49)	(1.00)	(1.00)	(0.71)	(0.42)	(0.20)	(0.35)
β	−0.438	1.343*	0.000	0.000	−0.614	−0.691	1.661*	0.358
	(0.86)	(0.39)	(1.00)	(1.00)	(0.61)	(0.37)	(0.18)	(0.23)
α	−0.315	−0.422	0.000	0.000	−1.152	−0.921*	−0.366*	−0.431
	(0.35)	(0.46)	(1.00)	(1.00)	(0.82)	(0.39)	(0.12)	(0.24)
AIC	−103.839	1.672	6.039	6.037	−11.457	−10.542	2.188	−121.356
TVP-Rotated Gumbel								
ω	1.631*	−1.018*	0.452	−1.925	1.585*	−0.467*	−1.456*	−0.282*
	(0.25)	(0.39)	(2.41)	(1.85)	(0.40)	(0.18)	(0.55)	(0.09)
β	−0.744*	1.249*	−0.254	1.689	−0.945*	0.831*	1.662*	0.689*
	(0.24)	(0.32)	(2.49)	(1.86)	(0.40)	(0.11)	(0.48)	(0.05)
α	−0.442	−0.170	−0.247	0.653	−0.910*	−0.425*	−0.296	−0.236
	(0.36)	(0.19)	(0.51)	(0.50)	(0.44)	(0.19)	(0.17)	(0.13)
AIC	−102.865	−14.994	4.779	5.492	−10.690	−32.629	2.321	−149.876
TVP-BB7								
ω_θ	1.841*	1.313*	1.006	0.667*	−0.037	0.645	−0.132	1.473*
	(0.00)	(0.27)	(0.64)	(0.31)	(0.25)	(0.42)	(1.42)	(0.15)
β_θ	−0.227*	−1.119*	−0.332	0.000	1.131	0.630	−0.632*	0.835*
	(0.00)	(0.46)	(0.63)	(0.68)	(0.74)	(0.38)	(0.29)	(0.34)
α_θ	−0.980*	−0.951*	−0.792*	−0.667*	−0.452*	−0.989*	0.438	−1.008*
	(0.00)	(0.35)	(0.25)	(0.15)	(0.18)	(0.31)	(1.36)	(0.13)
ω_δ	0.723*	0.641*	0.001	−0.267*	−0.722*	0.838*	−0.230*	0.537*
	(0.10)	(0.10)	(0.66)	(0.13)	(0.00)	(0.15)	(0.11)	(0.05)

Table 7 (*continued*)

Copula	Brazil	Chile	Colombia	India	Mexico	Russia	South Africa	Turkey
β_δ	−0.480	−0.256	−0.003	0.862*	0.553*	−0.886	0.317	−0.484*
	(0.30)	(0.15)	(1.01)	(0.22)	(0.01)	(0.48)	(0.26)	(0.19)
α_δ	−0.011	−1.332*	0.029	1.042*	1.741*	−0.745*	−1.471*	0.552*
	(0.10)	(0.20)	(0.79)	(0.17)	(0.02)	(0.30)	(0.61)	(0.03)
AIC	−118.234	−6.782	11.823	11.387	−7.439	−21.975	6.754	**−153.179**

Notes: See notes for Table 6.

Panel A. USD exchange rate against the local currency.

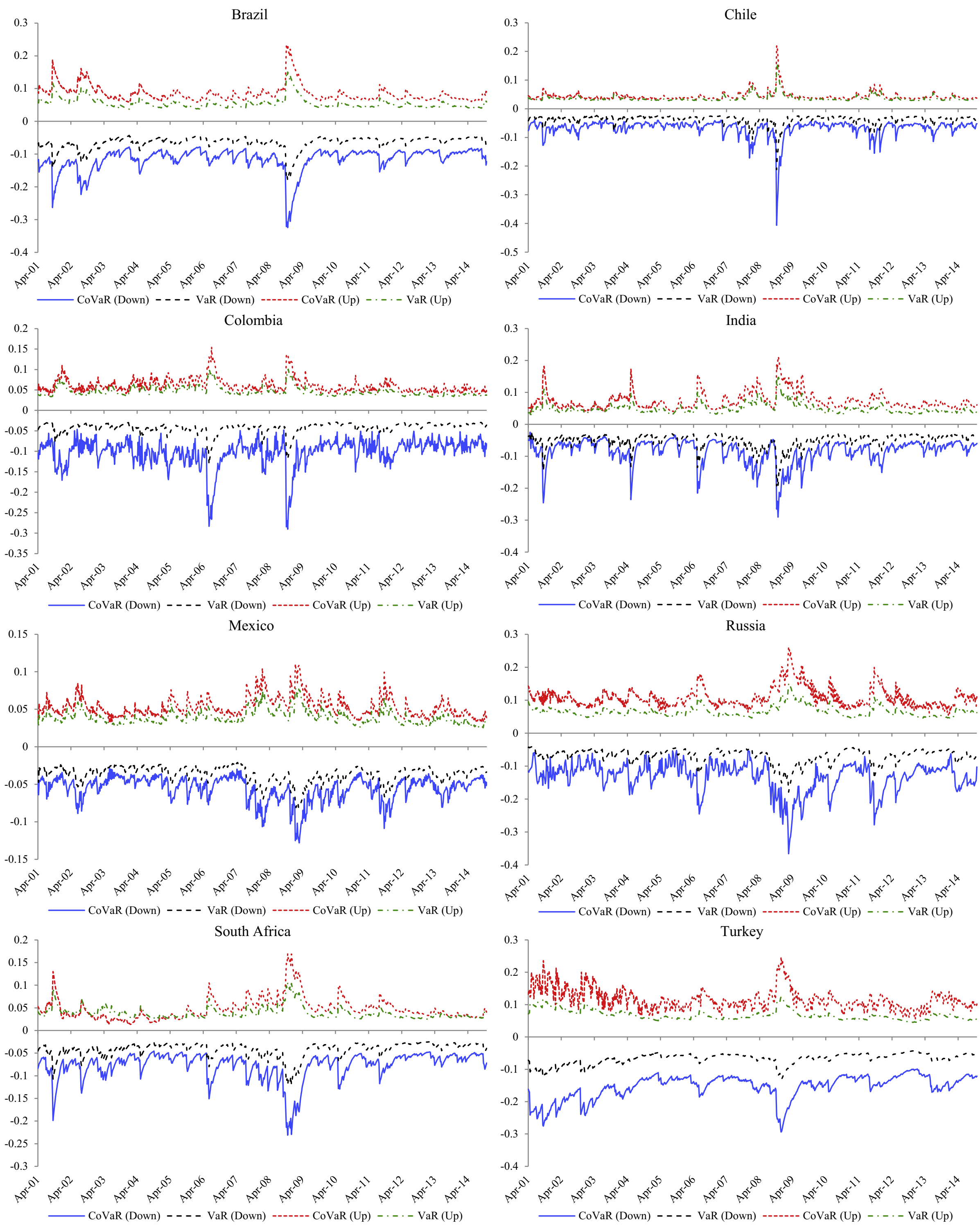

Fig. 3. Upside and downside value-at-risk (VaR) and conditional value-at-risk (CoVaR) for stock market returns.

Panel B. EUR exchange rate against the local currency.

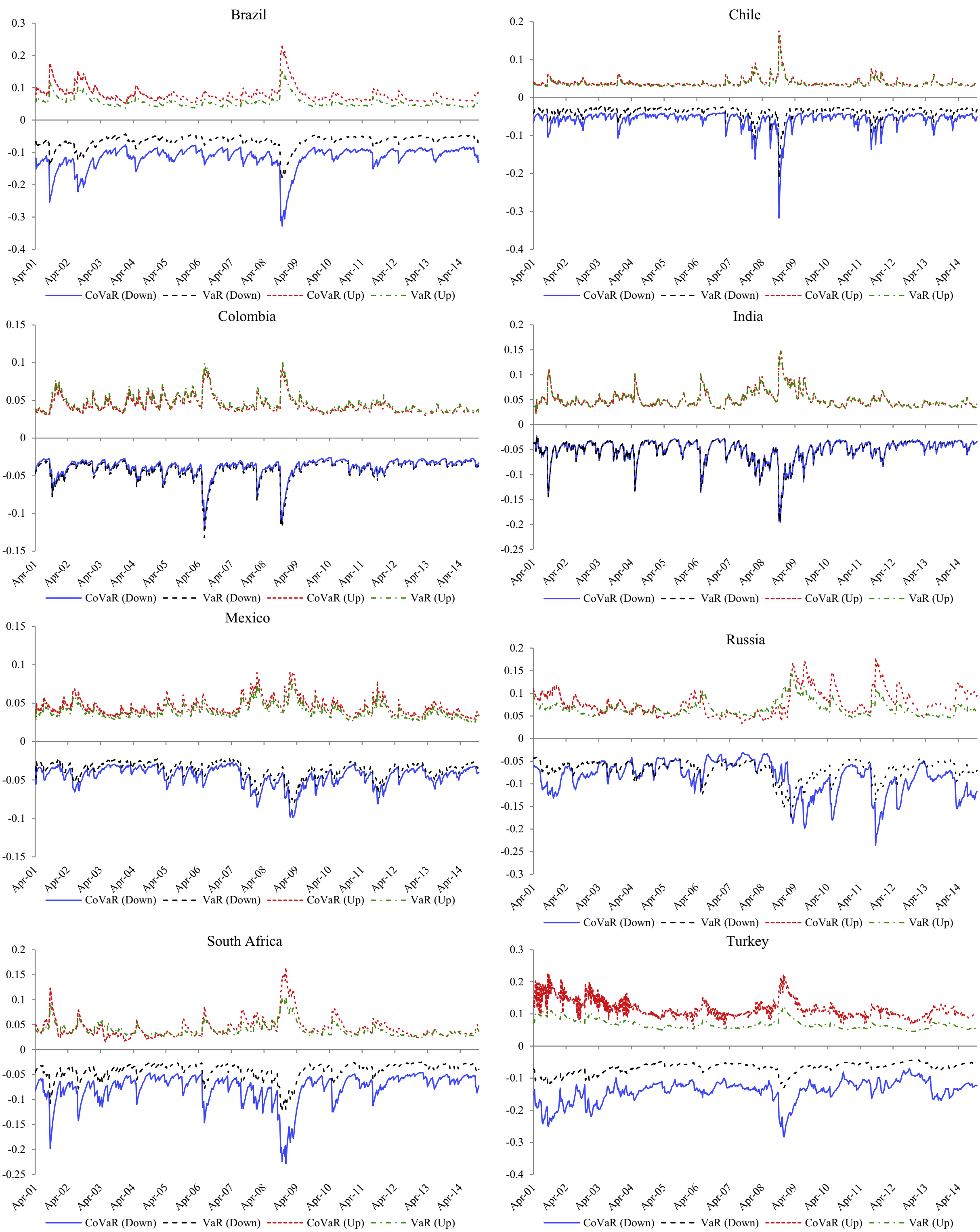

Fig. 3 (*continued*)

the EUR to the stock markets. This graphical evidence is corroborated by the KS statistic reported in Panel B in Table 8. Hence, in most of the counties analyzed, extreme depreciation of the local currency against the EUR had a major impact on stock market downside risk. As for upside risk, the empirical evidence is also rather mixed as there is more abundant evidence of upper tail independence. According the results of the KS statistic (Panel B, Table 8), Chile, Colombia and India exhibited no upside spillover effects from the EUR exchange rate to stock markets, whereas upside spillover effects were evident for the remaining countries.

Table 8
Descriptive statistics and tests for downside and upside value-at-risk (VaR) and conditional value-at-risk (CoVaR) for stock returns.

	Downside			Upside		
	VaR	CoVaR	H_0: CoVaR = VaR H_1: CoVaR < VaR	VaR	CoVaR	H_0: CoVaR = VaR H_1: CoVaR > VaR
Panel A. USD exchange rate against the local currency						
Brazil	−0.065	−0.116	0.883	0.055	0.085	0.794
	(0.020)	(0.036)	[0.000]	(0.016)	(0.026)	[0.000]
Chile	−0.037	−0.067	0.824	0.037	0.044	0.528
	(0.015)	(0.029)	[0.000]	(0.012)	(0.016)	[0.000]
Colombia	−0.042	−0.102	0.903	0.046	0.060	0.498
	(0.013)	(0.034)	[0.000]	(0.012)	(0.017)	[0.000]
India	−0.051	−0.084	0.563	0.050	0.073	0.547
	(0.022)	(0.037)	[0.000]	(0.017)	(0.027)	[0.000]
Mexico	−0.036	−0.056	0.618	0.039	0.053	0.530
	(0.011)	(0.016)	[0.000]	(0.009)	(0.013)	[0.000]
Russia	−0.069	−0.132	0.748	0.066	0.109	0.750
	(0.021)	(0.045)	[0.000]	(0.016)	(0.031)	[0.000]
South Africa	−0.042	−0.077	0.773	0.039	0.048	0.255
	(0.016)	(0.030)	[0.000]	(0.013)	(0.025)	[0.000]
Turkey	−0.068	−0.154	0.941	0.068	0.116	0.733
	(0.017)	(0.037)	[0.000]	(0.015)	(0.032)	[0.000]
Panel B. EUR exchange rate against the local currency						
Brazil	−0.065	−0.116	0.882	0.055	0.079	0.694
	(0.020)	(0.036)	[0.000]	(0.016)	(0.025)	[0.000]
Chile	−0.037	−0.058	0.788	0.037	0.040	0.344
	(0.015)	(0.023)	[0.000]	(0.012)	(0.013)	[0.241]
Colombia	−0.042	−0.039	0.000	0.046	0.043	0.000
	(0.013)	(0.012)	[0.999]	(0.012)	(0.011)	[0.999]
India	−0.051	−0.051	0.023	0.050	0.045	0.016
	(0.022)	(0.022)	[0.692]	(0.017)	(0.017)	[0.864]
Mexico	−0.036	−0.045	0.324	0.039	0.045	0.291
	(0.011)	(0.013)	[0.000]	(0.009)	(0.011)	[0.000]
Russia	−0.069	−0.086	0.292	0.066	0.078	0.252
	(0.021)	(0.036)	[0.000]	(0.016)	(0.028)	[0.000]
South Africa	−0.042	−0.077	0.769	0.039	0.044	0.124
	(0.016)	(0.030)	[0.000]	(0.013)	(0.021)	[0.000]
Turkey	−0.068	−0.141	0.869	0.068	0.116	0.800
	(0.017)	(0.035)	[0.000]	(0.015)	(0.029)	[0.000]

Notes: Standard errors for VaR and CoVaR are in brackets. *P* values for the Kolmogorov–Smirnov (KS) statistic are in square brackets.

Hence, extreme appreciation of their local currencies for most of the countries was accompanied by extreme (upward) movements in their stock prices.

5.4. Stock return spillover effects to exchange rates

Fig. 4 depicts the temporal dynamics of our results for the downside and upside VaR and CoVaR values for exchange rates by considering spillover effects from stock prices to exchange rates; while Table 9 reports summary statistic and hypotheses tests.

The temporal dynamics of downside and upside VaR and CoVaR for the USD exchange rate, considering the effect of stock returns, is represented in Panel A in Fig. 4. The graphical evidence shows that the VaR and CoVaR values shared a similar trend, although, at specific moments in time, they differed in that downside CoVaR abruptly fell or upside CoVaR picked up in most of the countries. Analyzing downside risk, our evidence shows that CoVaR values were significantly and systematically lower than VaR values for all countries, implying that stock prices had a systemic impact on exchange rates: extreme stock price depletion was accompanied by local currency depreciation, a result corroborated by the KS statistic data reported in Panel A in Table 9. This evidence may be explained on the basis that a considerable reduction in stock market value incentivized capital outflows from emerging markets to other markets due to the flight-to-quality phenomenon, thereby greatly reducing the value of the home currency. This evidence on downside spillover effects is consistent with the empirical evidence reported by Cho et al. (2016), Richards (2005) and Griffin et al. (2004).

As for upside risk, we also found spillover effects of stock prices on the USD exchange rate for all the countries, although for Chile and Colombia the spillover effects were smaller than for the remaining emerging economies. The KS statistic data for upside risk reported in Panel A in Table 9 corroborates this graphical evidence. This means that extreme upwards movements in stock prices had a positive impact on the local currency—possibly the outcome of internal capital movements induced by stock valuations in emerging economies. This evidence is consistent with that reported for exchange rate models (Branson, 1993; Frankel, 1983) and international investor portfolio rebalancing models (Hau and Rey, 2006; Pavlova and Rigobon, 2007).

Downside and upside VaR and CoVaR temporal dynamics for the EUR in different countries is presented in Panel B in Fig. 4. The dynamics and size of the VaR and CoVaR were different from those observed for the USD. Regarding downside risk, our evidence indicates that there were spillover effects from stock markets to the EUR exchange rate in all countries, except in Colombia and India, whose exchange rate markets exhibited no tail dependence regarding their stock markets; hence, extreme downside movements in these stock markets had no downside risk spillover effects on the value of the respective currencies against the EUR. For the remaining countries, the KS statistic data reported in Panel B in Table 9 corroborates the major drop in stock market value related with depreciation of the local currency against the EUR; this may be explained in terms of capital outflows boosted by low stock market valuations (see Cho et al., 2016; Richards, 2005; Griffin et al., 2004). Considering upside risk, we again found no evidence of spillover effects in Colombia and India and evidence

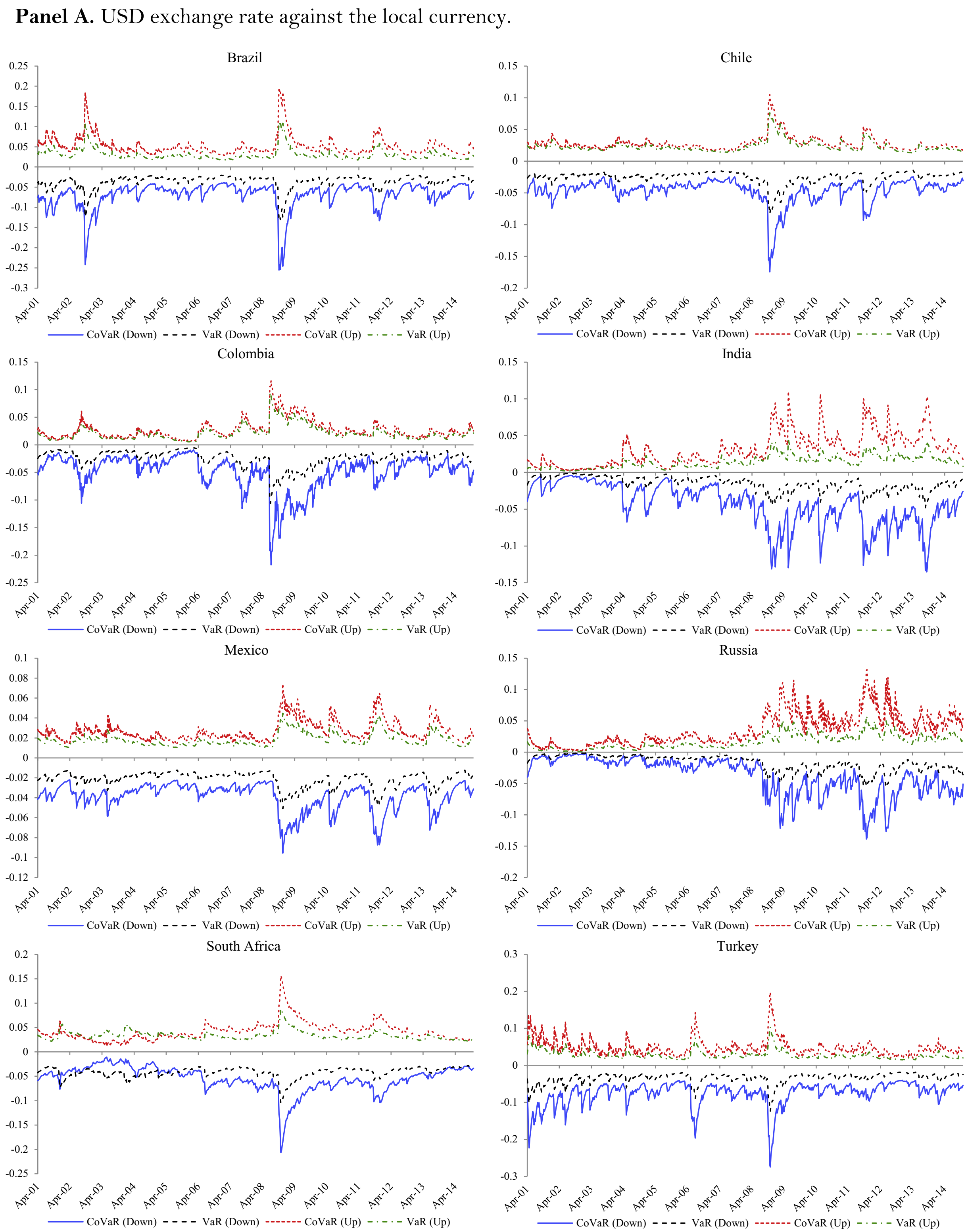

Fig. 4. Upside and downside value-at-risk (VaR) and conditional value-at-risk (CoVaR) for exchange rate returns.

of spillover effects for the remaining countries. Hence, extreme upward movements in stock prices led to an appreciation of the local currency against the EUR, which, as for the USD, can be explained by capital movements generated by excessively high stock prices in the emerging economies. This evidence is corroborated by the KS statistic results reported in Panel B in Table 9.

5.5. Asymmetric spillover effects

Although the impact of extreme movements on stock prices on exchange rates and vice versa are symmetric at the theoretical level, the reaction of real and financial flows to stock and currency prices cannot be symmetric for several reasons, among them, the

Panel B. EUR exchange rate against the local currency.

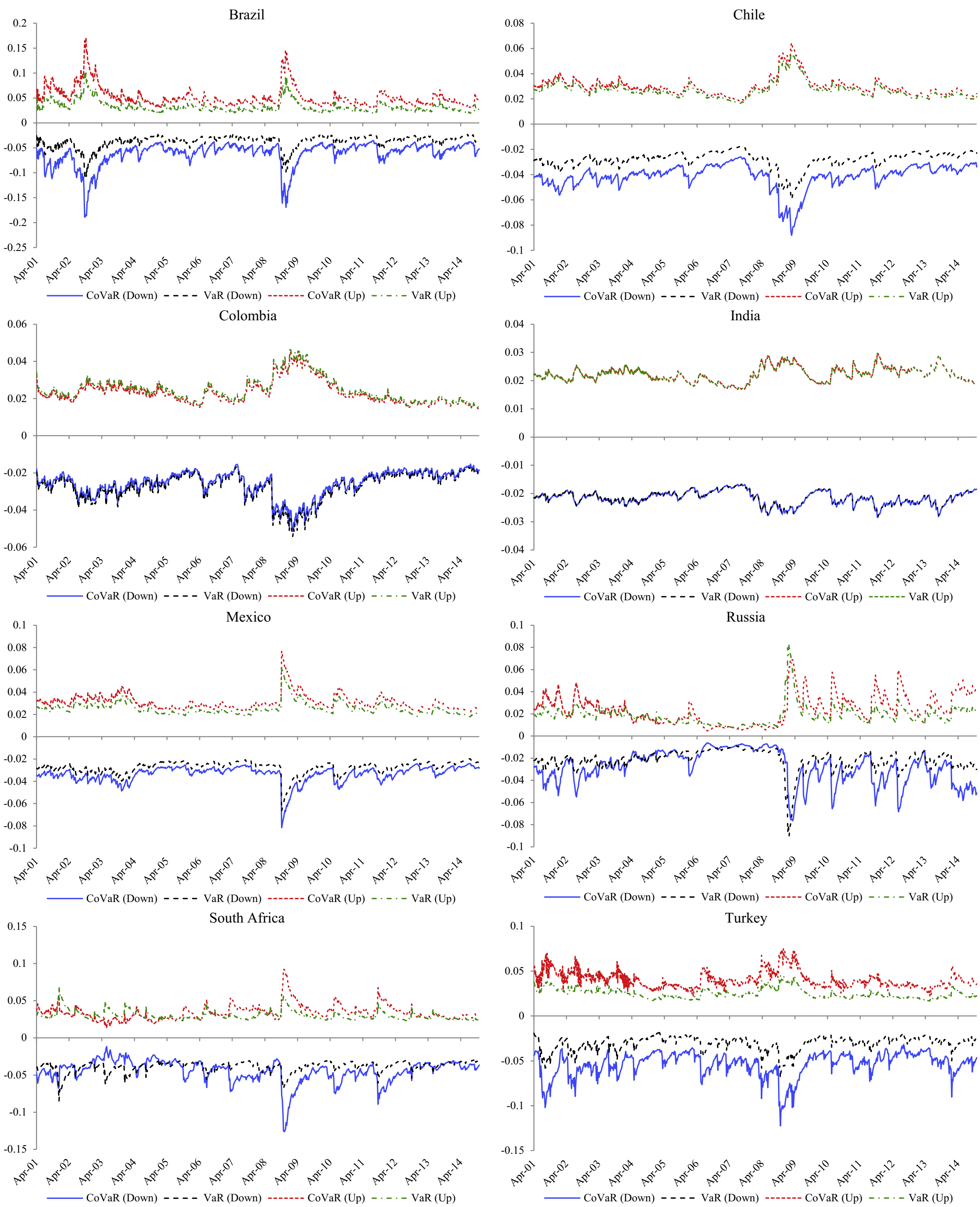

Fig. 4 (*continued*)

flight-to-quality effect.[7] Hence, upside and downside risk spillover effects may be asymmetric and different across currencies. Asymmetric spillovers have crucial implications for hedging decisions in international investor portfolios. In the next section we examine the existence of asymmetries in downside/upside spillovers and in spillover effects using the USD and EUR currency denomination.

5.5.1. Asymmetric downside–upside risk spillover effects

We examined asymmetric downside/upside risk spillover effects by testing for significant differences between the downside

[7] Asymmetric effects may also emerge empirically when tail dependence is symmetric and marginal distributions are asymmetric, given that CoVaR values depend on both the joint and marginal distributions (as stated in the two-step procedure described above).

Table 9
Descriptive statistics and tests for downside and upside value-at-risk (VaR) and conditional value-at-risk (CoVaR) for exchange rate returns.

	Downside			Upside		
	VaR	CoVaR	H_0: CoVaR = VaR H_1: CoVaR < VaR	VaR	CoVaR	H_0: CoVaR = VaR H_1: CoVaR > VaR
Panel A. USD exchange rate against the local currency						
Brazil	−0.036	−0.069	0.762	0.031	0.052	0.642
	(0.017)	(0.032)	[0.000]	(0.014)	(0.024)	[0.000]
Chile	−0.025	−0.046	0.766	0.023	0.028	0.343
	(0.010)	(0.019)	[0.000]	(0.009)	(0.011)	[0.000]
Colombia	−0.023	−0.048	0.518	0.021	0.027	0.190
	(0.015)	(0.031)	[0.000]	(0.013)	(0.017)	[0.000]
India	−0.015	−0.044	0.554	0.014	0.031	0.437
	(0.010)	(0.029)	[0.000]	(0.009)	(0.022)	[0.000]
Mexico	−0.021	−0.039	0.721	0.018	0.027	0.498
	(0.007)	(0.014)	[0.000]	(0.007)	(0.010)	[0.000]
Russia	−0.017	−0.037	0.357	0.017	0.036	0.339
	(0.012)	(0.029)	[0.000]	(0.012)	(0.026)	[0.000]
South Africa	−0.042	−0.055	0.385	0.034	0.042	0.330
	(0.011)	(0.026)	[0.000]	(0.009)	(0.019)	[0.000]
Turkey	−0.035	−0.076	0.808	0.028	0.048	0.587
	(0.015)	(0.032)	[0.000]	(0.012)	(0.023)	[0.000]
Panel B. EUR exchange rate against the local currency						
Brazil	−0.037	−0.062	0.722	0.032	0.052	0.650
	(0.013)	(0.024)	[0.000]	(0.012)	(0.020)	[0.000]
Chile	−0.028	−0.041	0.745	0.027	0.030	0.281
	(0.007)	(0.010)	[0.000]	(0.007)	(0.007)	[0.000]
Colombia	−0.027	−0.026	0.000	0.025	0.023	0.000
	(0.007)	(0.007)	[0.999]	(0.006)	(0.006)	[0.999]
India	−0.022	−0.022	0.032	0.022	0.022	0.035
	(0.002)	(0.002)	[0.476]	(0.003)	(0.003)	[0.410]
Mexico	−0.028	−0.034	0.489	0.025	0.031	0.468
	(0.006)	(0.007)	[0.000]	(0.006)	(0.007)	[0.000]
Russia	−0.021	−0.028	0.330	0.019	0.024	0.307
	(0.010)	(0.015)	[0.000]	(0.009)	(0.013)	[0.000]
South Africa	−0.038	−0.045	0.289	0.030	0.034	0.247
	(0.007)	(0.015)	[0.000]	(0.006)	(0.010)	[0.000]
Turkey	−0.030	−0.054	0.804	0.025	0.040	0.784
	(0.008)	(0.014)	[0.000]	(0.006)	(0.009)	[0.000]

Notes: Standard errors for VaR and CoVaR are in brackets. P values for the Kolmogorov–Smirnov (KS) statistic are in squared brackets.

CoVaR normalized by the downside VaR and the upside CoVaR normalized by the upside VaR, considering the USD and EUR currency denominations. We used the KS statistic to test for significant differences between downside and upside spillovers.

Considering spillovers from exchange rates to stock markets, the results of the KS test reported in Panel A in Table 10 provide evidence of asymmetric downside and upside risk spillover effects: the downside spillovers measured by the normalized CoVaR values were greater than the upside spillovers, independently of the currency denomination used. An exception was Colombia, where upside and downside risk spillovers for the EUR were of similar size, given that the KS statistic was not able to reject the null hypothesis.

Regarding spillovers from stock markets to exchange rate returns, the results of the KS test reported in Panel B in Table 10 provide evidence of asymmetric spillover effects in all countries using the USD currency denomination, with downside risk spillovers significantly greater than upside risk spillovers. However, for the EUR denomination, we found evidence of asymmetries for all the countries except Colombia, India and Russia, where symmetric spillovers were observed.

Our results on spillover asymmetries—which is consistent with the evidence reported by Wang et al. (2013) for regimes where local currency values are negatively correlated with the USD and stock returns—point to the presence of different stock market sensitivities to home currency appreciation or depreciation and of different exchange rate sensitivities to bullish and bearish stock markets in emerging economies. This may be explained by the asymmetric reaction of real and financial flows when markets are bullish and bearish, with these flows reinforcing downside risk spillovers to a greater extent than upside risk spillovers. Our results are consistent with the fact that bearish financial markets in emerging economies trigger capital outflows with a greater impact on exchange rates than that of capital inflows attracted by bullish stock markets. This evidence would indicate the advisability of asymmetric hedging strategies by international investors in emerging markets.

5.5.2. Asymmetric currency spillover risk effects

We examined whether downside and upside spillover risks differ across currencies by testing—using the KS statistic—for significant differences between the downside CoVaR normalized by the downside VaR using the USD and the downside CoVaR normalized by the downside VaR using the EUR.

Considering spillovers from exchange rates to stock markets, the results of the KS test reported in Panel A in Table 11 provide evidence of asymmetric downside and upside risk spillover effects, as the downside spillovers measured by the normalized CoVaR values were significantly greater for the USD than for the EUR for all the countries except Brazil and South Africa. As for upside risk, our results indicate this was significantly greater for the USD than for the EUR. These results are consistent with the fact that the USD plays a more crucial role than the EUR in trade and financial transactions in the emerging economies studied here.

Analyzing spillovers from stock markets to currency markets, the evidence provided by the KS test reported in Panel B in Table 11 indicates that the size of both downside and upside spillover risk was greater for the USD than for the EUR.

Table 10
Asymmetric downside–upside risk spillover effects.

	USD H_0: $\frac{CoVaR}{Var}$(Down) = $\frac{CoVaR}{Var}$(Up) H_1: $\frac{CoVaR}{Var}$(Down) > $\frac{CoVaR}{Var}$(Up)	EUR H_0: $\frac{CoVaR}{Var}$(Down) = $\frac{CoVaR}{Var}$(Up) H_1: $\frac{CoVaR}{Var}$(Down) > $\frac{CoVaR}{Var}$(Up)
Panel A. Spillover effects from currency to stock returns		
Brazil	1.000	1.000
	[0.000]	[0.000]
Chile	0.987	1.000
	[0.000]	[0.000]
Colombia	0.948	0.000
	[0.000]	[0.999]
India	0.628	0.994
	[0.000]	[0.000]
Mexico	0.726	0.997
	[0.000]	[0.000]
Russia	0.735	0.240
	[0.000]	[0.000]
South Africa	0.994	1.000
	[0.000]	[0.000]
Turkey	1.000	0.798
	[0.000]	[0.000]
Panel B. Spillover effects from stock to currency returns		
Brazil	1.000	0.422
	[0.000]	[0.000]
Chile	0.986	1.000
	[0.000]	[0.000]
Colombia	0.951	0.000
	[0.000]	[0.999]
India	0.917	0.000
	[0.000]	[0.999]
Mexico	1.000	0.240
	[0.000]	[0.000]
Russia	0.152	0.032
	[0.000]	[0.467]
South Africa	0.275	0.097
	[0.000]	[0.000]
Turkey	1.000	0.546
	[0.000]	[0.000]

Table 11
Asymmetric risk spillovers by currency denomination.

	Downside H_0: $\frac{CoVaR}{Var}$ [\$] = $\frac{CoVaR}{Var}$ [€] H_1: $\frac{CoVaR}{Var}$ (\$) > $\frac{CoVaR}{Var}$ (€)	Upside H_0: $\frac{CoVaR}{Var}$ (\$) = $\frac{CoVaR}{Var}$ (€) H_1: $\frac{CoVaR}{Var}$ (\$) > $\frac{CoVaR}{Var}$ (€)
Panel A. Spillover effects from currency to stock returns		
Brazil	0.192	0.958
	[0.167]	[0.000]
Chile	0.812	0.862
	[0.000]	[0.000]
Colombia	1.000	1.000
	[0.000]	[0.000]
India	0.994	0.996
	[0.000]	[0.000]
Mexico	0.984	0.987
	[0.000]	[0.000]
Russia	0.779	0.721
	[0.000]	[0.000]
South Africa	0.241	0.364
	[0.172]	[0.000]
Turkey	0.808	0.209
	[0.000]	[0.000]
Panel B. Spillover effects from stock to currency returns		
Brazil	0.994	0.825
	[0.000]	[0.000]
Chile	0.966	0.893
	[0.000]	[0.000]
Colombia	1.000	1.000
	[0.000]	[0.000]
India	1.000	0.996
	[0.000]	[0.000]
Mexico	1.000	0.993
	[0.000]	[0.000]
Russia	0.804	0.825
	[0.000]	[0.000]
South Africa	0.319	0.324
	[0.000]	[0.000]
Turkey	0.999	0.402
	[0.000]	[0.000]

Lower spillover effects from the EUR than from the USD and the absence of spillover effects for the EUR in some emerging economies may be explained by the fact that the EUR, compared to the USD, plays a minor role in trade and especially in financial transactions. We also observed that, for the USD compared to the EUR, downside and upside CoVaR values were lower and higher, respectively. Given that exchange rate volatilities for the USD and EUR were similar, the differences may also be explained by the relative importance of the USD in those emerging economies.

6. Conclusions

Stock and exchange rate markets are naturally linked given that changes in currency values have an impact on trade flows and that stock price movements have an impact on capital movements. We studied the relationship between stock and currency returns in a selection of emerging economies, paying particular attention to downside and upside risk spillovers from exchange rates to stock prices and vice versa.

We characterized co-movement between stock and exchange rate markets using copulas, measuring downside and upside risk spillovers from one market to the other by computing downside and upside CoVaR and assessing spillover effects by testing for significant differences between the CoVaR and VaR values. For a sample period running from April 2001 to November 2014 and using a selection of emerging economies, namely, Brazil, Chile, Colombia, India, Mexico, Russia, South Africa and Turkey, we found evidence of a positive relationship between stock prices and currency values with respect to the USD and the EUR; thus, the home currencies appreciated (depreciated) when stock prices moved up (down). Furthermore, we found evidence of downside and upside spillover risk effects from currencies to stock returns and from stock returns to currency returns; this is consistent with the fact that bullish (bearish) stock markets attract capital inflows as demand for local assets by foreign investors increases (decreases), thus increasing (reducing) the value of the domestic currency. This evidence casts doubts on the usefulness of foreign exchange restrictions aimed at isolating a domestic capital market from global influences. Our evidence is also consistent with the fact that the increase in international trade in emerging economies has strengthened financial integration in spite of capital movement restrictions.

Our analysis reveals that downside and upside spillovers are asymmetric, with greater downside rather than upside risk spillover effects. We also found that spillovers from and to the USD were greater than from and to the EUR. This evidence is consistent with the fact that the USD plays a more crucial role than the EUR in trade and financial transactions in emerging economies. Our downside risk results are consistent with flight-to-quality, and our downside and upside risk analysis has practical implications for downside and upside risk management of international investor portfolios for emerging markets.

Acknowledgements

We gratefully thank the Editor, Carol Alexander, and two anonymous referees for providing useful comments and suggestions that have improved the quality of the paper. Juan C. Reboredo acknowledges financial support provided by the Xunta de Galicia and FEDER under research grant GPC2013-045. Andrea Ugolini acknowledges the financial support of the project MIUR PRIN MISURA – Multivariate models for risk assessment.

References

Abadie, A., 2002. Bootstrap tests for distributional treatment effects in instrumental variables models. Journal of American Statistical Association 97 (457), 284–292.

Abdalla, I.S.A., Murinde, V., 1997. Exchange rate and stock price interactions in emerging financial markets: evidence on India, Korea, Pakistan, and Philippines. Applied Financial Economics 7, 25–35.

Adrian, T., Brunnermeier, M.K., 2011. CoVaR. NBER working paper series, w17454.

Ajayi, R.A., Friedman, J., Mehdian, S.M., 1998. On the relationship between stock returns and exchange rates: test of Granger causality. Global Finance Journal 9, 241–251.

Aloui, C., 2007. Price and volatility spillovers between exchange rates and stock indexes for the pre- and post-euro period. Quantitative Finance 7, 669–685.

Bernal, O., Gnabo, J.-Y., Guilmin, G., 2014. Assessing the contribution of banks, insurance and other financial services to systemic risk. Journal of Banking and Finance 47, 270–287.

Billio, M., Getmansky, M., Lo, A.W., Pelizzon, L., 2012. Econometric measures of systemic risk in the finance and insurance sectors. Journal of Financial Economics 104, 535–559.

Bisias, D., Flood, M., Loo, A.W., Valavanis, S., 2012. A Survey of Systemic Risk Analytics. Office of Financial Research, US Department of the Treasury, Working paper #1.

Branson, W.H., 1993. Macroeconomic determinants of real exchange risk. In: Herring, R.J. (Ed.), Managing Foreign Exchange Risk. Cambridge University Press, Cambridge, MA.

Breymann, W., Dias, A., Embrechts, P., 2003. Dependence structures for multivariate high-frequency data in finance. Quantitative Finance 3, 1–16.

Cho, J.-W., Choi, J.H., Kim, T., Kim, W., 2016. Flight-to-quality and correlation between currency and stock returns. Journal of Banking and Finance 62, 191–212.

Chow, E.H., Lee, W.Y., Solt, M.S., 1997. The exchange rate risk exposure of asset returns. Journal of Business 70, 105–123.

Diamandis, P., Drakos, A., 2011. Financial liberalization, exchange rates and stock prices: exogenous shocks in four Latin America countries. Journal of Policy Modeling 33, 381–394.

Dornbusch, R., Fischer, S., 1980. Exchange rates and the current account. American Economic Review 70, 960–971.

Frankel, J.A., 1983. Monetary and portfolio-balance models of exchange rate determination. In: Bhandari, J.S., Putnam, B.H. (Eds.), Economic Interdependence and Flexible Exchange Rates. MIT Press, Cambridge, MA.

Froot, K., O'Connell, P., Seasholes, M., 2001. The portfolio flows of international investors. Journal of Financial Economics 59, 151–193.

Gavin, M., 1989. The stock market and exchange rate dynamics. Journal of International Money and Finance 8, 181–200.

Girardi, G., Ergün, A.T., 2013. Systemic risk measurement: multivariate GARCH estimation of CoVaR. Journal of Banking and Finance 37, 3169–3180.

Granger, C.W.J., Huang, B.N., Yang, C.W., 2000. A bivariate causality between stock prices and exchange rates: evidence from recent Asian flu. The Quarterly Review of Economics and Finance 40, 337–354.

Griffin, J.M., Nardari, F., Stulz, R.M., 2004. Are daily cross-border equity flows pushed or pulled? Review of Economics and Statistics 86 (3), 641–657.

Hau, H., Rey, H., 2006. Exchange rates, equity prices, and capital flows. The Review of Financial Studies 19, 273–317.

Joe, H., 1997. Multivariate models and dependence concepts. In: Monographs in Statistics and Probability 73. Chapman and Hall, London.

Joe, H., Xu, J.J., 1996. The Estimation Method of Inference Functions for Margins for Multivariate Models Technical Report No. 166. Department of Statistics, University of British Columbia.

Lin, F., 2011. Tail Dependence between Stock Index Returns and Foreign Exchange Rate Returns—A Copula Approach. Available at SSRN: <http://ssrn.com/abstract=1931726> or <http://dx.doi.org/10.2139/ssrn.1931726>.

Lin, C.-H., 2012. The comovement between exchange rates and stock prices in the Asian emerging markets. International Review of Economics and Finance 22, 161–172.

Michelis, L., Ning, C., 2010. The dependence structure between the Canadian stock market and the USD/CAD exchange rate: a copula approach. Canadian Journal of Economics 43, 1016–1039.

Nelsen, R.B., 2006. An Introduction to Copulas. Springer-Verlag, New York.

Nieh, C.-C., Lee, C.-F., 2001. Dynamic relationship between stock prices and exchange rates for G-7 countries. The Quarterly Review of Economics and Finance 41, 477–490.

Ning, C., 2010. Dependence structure between the equity market and the foreign exchange market – a copula approach. Journal of International Money and Finance 29, 743–759.

Pan, M.S., Fok, R., Liu, Y., 2007. Dynamic linkages between exchange rates and stock prices: evidence from East Asian markets. International Review of Economics and Finance 16, 503–520.

Patton, A.J., 2006. Modelling asymmetric exchange rate dependence. International Economic Review 47 (2), 527–556.

Pavlova, A., Rigobon, R., 2007. Asset prices and exchange rates. Review of Financial Studies 20 (4), 1139–1181.

Phylaktis, K., Ravazolo, F., 2005. Stock prices and exchange rate dynamics. Journal of International Money and Finance 24, 1031–1053.

Poon, S., Rockinger, M., Tawn, J., 2004. Extreme value dependence in financial markets: diagnostics, models, and financial implications. Review of Financial Studies 17, 581–610.

Reboredo, J.C., 2011. How do crude oil prices co-move? A copula approach. Energy Economics 33, 948–955.

Reboredo, J.C., 2012. Modelling oil price and exchange rate co-movements. Journal of Policy Modeling 34 (3), 419–440.

Reboredo, J.C., 2013. Is gold a safe haven or a hedge for the US dollar? Implications for risk management. Journal of Banking and Finance 37, 2665–2676.

Reboredo, J.C., Ugolini, A., 2015. Systemic risk in European sovereign debt markets: a CoVaR-copula approach. Journal of International Money and Finance 51, 214–244.

Richards, A., 2005. Big fish in small ponds: the trading behavior and price impact of foreign investors in Asian emerging equity markets. Journal of Financial and Quantitative Analysis 40, 1–27.

Sklar, A., 1959. Fonctions de Riépartition á n Dimensions et Leurs Marges. Publications de l'Institut Statistique de l'Université de Paris 8, 229–231.

Wang, Y.-C., Wu, J.-L., Lai, Y.-H., 2013. A revisit to the dependence structure between the stock and foreign exchange markets: a dependence switching copula approach. Journal of Banking and Finance 37, 1706–1719.

Yang, S.Y., Doong, S.C., 2004. Price and volatility spillovers between stock prices and exchange rates: empirical evidence from the G-7 countries. International Journal of Business and Economics 3, 139–153.