Tail Risks and Domino Patterns in Financial Markets*

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Abstract

We identify new structural channels for the transmission of shocks in emerging currencies, and develop a model in which shock propagations evolving from domestic emerging stock markets, liquidity (banks' credit default swaps), credit risk (Volatility Index) and growth (commodity prices) channels disseminate to emerging market foreign exchanges. We quantify joint downside risks and document that these asset classes tend to experience concurrent extreme shocks. We measure the time-varying shock spillover intensities to ascertain a significant increase in cross-asset linkages during periods of high volatility which is over and above any expected economic fundamentals, providing strong evidence of asymmetric investor induced contagion, triggered by cross asset rebalancing. The critical role of the credit crisis is amplified, as the beginning of an important reassessment of emerging market currencies which lead to changes in the dependence structure, a revaluation and recalibration of their risk characteristics. By modelling tail risks we detect structural breaks and find patterns consistent with the domino effect.

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Keywords: Asymmetric Foreign Exchange Volatility, Emerging Markets, Tail Risk, Contagion Channels, Domino Effect, Copula Functions.

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1. Introduction

Over the last decade, emerging markets have been a magnet for global investors. Even pension funds and sovereign wealth funds have increased their allocations to emerging market assets in order to take advantage of the world's fastest growing economies. However, the financial crisis which began in industrialized countries during 2008 and quickly spread to emerging markets, deteriorated the environment for capital flows and triggered deep sell offs in emerging economies (see also Aloui et al. 2011; Samarakoon, 2011; Alsakka and Gwilym, 2012; Eichengreen et al. 2012; Semmler and Bernard, 2012 *inter alia*). The subprime mortgage crisis and the collapse of Lehman Brothers was followed by a synchronised explicit decline in emerging market currencies, over and above what one would expect from economic fundamentals.

Motivated by the lack of evidence that macroeconomic fundamentals serve as the determinants of co-movements in international markets (see also Longin and Solnik 2001; Ang and Chen 2002; Yuan, 2005; and Baur 2012, for informative readings), we examine how the recent credit crisis affected the behavior of the most liquid emerging currency markets and the importance of external shocks in shaping the movement of certain emerging currency markets. To assess the incremental impact of the credit crunch we split our sample in three sub-periods: before, during and after the financial turmoil. As a result, we are able to test for structural changes in the tail behavior of the unconditional distribution. Additionally, in order to generate a plausible counterfactual, we allow for other factors that may have played a crucial role in the behavior of emerging currencies and hence, in driving cross asset allocation. Specifically, we also evaluate the role of global liquidity shocks, credit risk fluctuations and advances in the commodity markets.

Allowing for the influence of these factors we also endeavour to answer the following questions: what is the impact of global financial shocks in emerging currencies? how is stability in emerging currencies shaped by cross-asset rebalancing? Are there any risk factors which have acted as channels of risk transfer on emerging currency markets? Is it possible to model risk spillovers in emerging currencies? Is there any structural change in the tail behaviour of the unconditional distribution? Is there any extreme value dependence with other financial assets? We address these essential issues to identify new channels and sources for the transmission of shocks across emerging market currencies and to verify how crises are likely to spread across emerging market foreign exchanges. Global financial shocks, like the recently experienced credit crunch, play an important role in driving financial activity in emerging economies. Nonetheless, the empirical literature is silent about the role and the extent to which global financial risk shocks drive fluctuations in emerging countries. Moreover, the role of portfolio balance effects in emerging currency markets remains rather controversial and the empirical evidence in its support rather indirect.

This study employs a distinct approach on emerging currency markets to determine portfolio balancing effects and new channels for the transmission of shocks on emerging market foreign exchanges. While there is extensive literature on studying comovements between the international equity markets and on modelling the dependence structure between exchange rates by using copulas, there is no literature on employing copulas to model the cross-asset dependence with several risk factors and the importance that external shocks have in shaping the movement of certain emerging currencies. We use the five most liquid and rapidly developed emerging markets (i.e. Brazil, Russia, India, Mexico and South Africa)[1]. These emerging economies constitute the epitome of -and benefited the most from- the macroeconomic tailwinds that boosted growth in 2003 – 2008 period, fuelled by declining

[1]Our initial sample incorporates Turkey, South Korea, Eastern European, and Latin American countries. In most cases, we identify a non-stationary process in the data, and thus a stochastic model with a drift and a noise/trend driving terms will provide a better explanation for the movement of these emerging currencies. We do not present the results here, because such a stochastic model is out of the scope of this study, and thus, we analyse the most representative emerging currencies which fit appropriate with copula functions. Further results are available upon request by the authors. Also, China, the most liquid and rapidly developed emerging market was excluded from our final sample due to the peg of its national currency with the U.S. Dollar.

interest rates in the developed world, the commodity supercycle of rising prices and higher commodity investments. We then construct four channels of risk transfer on emerging market currencies. In particular, we suggest that regardless of the macroeconomic fundamentals, investors substantially compose and alter their investments in emerging currency markets in response to shocks experienced in the following four channels: developments in liquidity, credit risk, growth and the information contained in domestic stock markets. Thus, emerging market foreign exchanges are mainly determined by changes in these channels, which are over and above what one would expect from economic fundamentals, resembling to portfolio balance effects and investor-induced contagion. The liquidity channel is characterized by changes in the iTraxx Senior Financial Index (i.e. the spread of Banks' Credit Default Swaps), the credit risk channel is associated with changes on the Volatility Index, stock markets are represented by the most representative domestic stock indexes, while the growth channel is interpreted by developments on the commodities (i.e. S&P Goldman Sachs Commodity Index).

We call these variables cross-asset rebalancing and contagion channels, that is, variables which can amplify shocks and lead to instability and whose extreme adverse realisations are associated with a slump of emerging market foreign exchanges. If there is a significant increase in cross-asset and cross-market linkages and co-movements during the crisis period, then we can infer that developments in these currencies are driven and determined by changes in these channels. Otherwise, the movements of these currencies are mainly driven by developments on macroeconomic fundamentals.

Additionally, we attempt to ascertain what these co-movements reflect in asset pricing and risk management terms. In particular, a further dimension to our study is to examine volatility spikes, the existence of any extreme value dependence, symmetries and asymmetries in the dependence structure and to investigate joint downward/upward dynamics and the contemporaneous dependence entailed in the tails. The recent credit crunch advanced on elevated volatility, large fluctuations and extreme exchange rate variations (i.e. tail risks). Investors pulled capital from emerging countries, even those with small levels of perceived risk, and caused values of stocks and domestic currencies to plunge, highlighting how sensitive to fluctuations and changes in economic and market conditions, emerging markets are. These events originate unprecedented losses to risk, portfolio managers and corporations. As Campbell et al., (2010) document, currencies play a crucial role in risk-minimising a diversified investment portfolio.

Moreover, measuring tail dependence and extreme co-movements boils down to the estimation of the probability of observing very large losses (Straetmans and Candelon, 2013; Dias 2014; Tolikas 2014) and thus it helps international investors to manage risks in their portfolio (Wang et al. 2013). Indeed, an increase in cross-asset co-movements diminishes rapidly diversification opportunities (Ibragimov and Walden, 2007) and renders traditional diversification theory fruitless (Markowitz, 1952; and Solnik, 1974). Thus, no risk management term has entered the vernacular of investors as rapidly as "tail risk management" has in the last years. As Ibragimov et al. (2013) observes, emerging country foreign exchanges are even more pronounced to external financial shocks than their developed counterparts and respond to external frequencies in a nonlinear way. Consequently, modelling and managing emerging market foreign exchange risk is a challenging and important issue in the financial decision – making process.

To address these fundamental issues empirically, the methodology we use in this study differs in a fundamental way from most of the methods used in the literature in analysing dependence and co-movements between exchange rates and other sets of risk factors. In particular, we employ and compare several copula functions[2] with different dependence structures (i.e. Gaussian, Student – *t*, and Joe-Clayton) to capture the risk in a large set of risk factors, to model and examine conditional and tail dependence between emerging market exchange rates, domestic stock markets, commodities (S&P Goldman Sachs Commodity Index), liquidity (Banks Credit Default Swaps)[3] and credit channels (Volatility Index)[4]. We split our sample into three sub-groups (before, during and after the financial crisis) to assess whether the crisis led to significant changes in the structural cross-asset transmission of shocks to emerging currencies, the dependence structure and in the likelihood of large variations in emerging market exchange rates.

Thus, the findings of our study are of importance for policy makers, asset managers, risk managers, investors and contribute in various ways in the existing literature. First, we find that in periods of crisis several financial assets experience synchronically dramatic losses. We find that emerging currency movements are the result from the interaction received by global liquidity and credit risk shocks and hence, we provide strong evidence of increased co-movements and extreme tail dependence during the crisis period. The significance of the tail dependence implies that these asset classes tend to experience concurrent extreme shocks. This finding has important risk and asset pricing implications, since risk measures which omit fatness of tails lead to serious underestimation of downside risk. Furthermore, left tail dependence indicates the potential of simultaneous large losses and allows investors to measure the probability of the extreme losses. The presence of risk

[2]We also employ Extreme Value Theory (EVT) to capture downside tail risks in these currencies (built in a portfolio structure) and their interaction with other risk factors. The ability of EVT to fit the fat tailed returns' distribution was poor (the p-value was low). As discussed by Tolikas (2014), it is possible EVT to provide a bad fit for the whole interval, "due to the changing nature of the distribution of the extremes which implies that a single distribution is unlikely to provide a good fit". Results are not presented for dimensionality reasons, and are available upon request by the authors.

[3]We also use the 3 month Libor rate as a proxy for liquidity, however BCDS provide a better fit for the dependence structure with emerging currencies and hence we analyse the findings from this index in this study.

[4]The Volatility Index (VIX) represents changes in credit market conditions similar and is used as a proxy for developments in credit risk, similar to the suggestions made by by Alexander and Kaeck, 2008, and Annaert et al. 2013.

spillovers among asset classes increases portfolio risk and magnifies the volatility of the expected returns in emerging market currencies. Hence, we compliment the works of Sarno and Schmeling (2014) who observe future fundamentals that drive exchange rates and Campbell et al., (2010), who identify currency risk-minimising strategies for global bond investors.

Second, our findings imply that accelerated decreases and large variations in the domestic stock markets, in the growth (i.e. commodities), liquidity (BCDS) and credit channels (i.e. VIX) lead to accelerated decreases and increased fluctuations in the emerging market foreign exchanges. This joint downside risk among these asset classes has not been documented in the literature of emerging market exchange rates. The increase in cross-asset co-movements diminishes rapidly diversification opportunities. Moreover, we observe that dependence remains significant but weaker after the financial crisis and that emerging market exchange rates become more pronouncedly heavy-tailed in downward moves than in upward moves. This finding indicates statistically decreases in the tail indices and structural breaks to these exchange rates due to the recent financial crisis that correspond to the increase in the likelihood of large fluctuations. As a result, on the post crisis period, emerging market foreign exchanges are more susceptible to financial crisis and speculative attacks. The increased likelihood of extreme joint losses suggests a higher than normal Value at Risk. These findings corroborate and extend the works of Aloui et al., (2011), Bubak et al., (2011), Sirr et al., (2011), Banti et al., (2012), Ulku and Demirci (2012), Tsai (2012), and Andreou et al., (2013), who investigate spillovers and the dependence structure between emerging currencies and stock markets.

Third, we document a significant increase in cross-asset linkages during periods of high volatility which is over and above any economic fundamental. Thus, we provide empirical evidence that large adverse shocks in the four channels described above, spill over to emerging market currencies triggered by cross-asset rebalancing, advancing to investor-induced contagion. Our explicit distinction between the four contagion channels and our modelling for the evolution of these crashes sheds new light on the propagation of large negative cross-asset returns, corroborating and complementing the works of Yuan (2005), Boyer et al., (2006), Carlin et al., (2007), Dungey et al., (2010), Boyer (2011), and Jotikasthira et al., (2012), who observe that crisis spreads to other markets and investment funds through the liquidity channel. In addition, tail dependence and investor-induced contagion is a source of systemic risk and thus, we complement the works of Allen and Carletti (2013) and Liang (2013) who distinguish shocks in order to outline elements of systemic risk and to identify risks to global financial stability.

Fourth, we extend the works of Wang et al., (2013), Ibragimov et al., (2013), and Rossi and De Magistris (2013) who study tail risks and document asymmetric dependencies in emerging market currencies through liquidity channels. Interestingly, we observe the existence of significant dependence and partial comovement but asymmetric tail dependence for the pre- crisis, the crisis and the post- crisis periods, implying that there is asymmetry in upward moves for all emerging currencies considered, pointing to asymmetric contagion. These findings also, affect the pricing of emerging market currencies complimenting the work of Susmel (2001) who studies tail dependence pricing for safety – first investors. Fifth, we find that the local contagion channels spread the crisis in a domino fashion in the emerging market currencies, corroborating the work of Markwat et al., (2009) who observe domino effects among international stock markets.

Sixth, the post-crisis asymmetric dependence between emerging currencies and the leading commodity index indicates that there is a structural shift in the behaviour of emerging currencies. Regularly, in the post-crisis period we expect a symmetric upward swing. However, we find that the structure of these emerging currencies altered by the credit crunch, implying significant changes in the structural transmission of shocks to emerging currencies. As a result, the credit crunch played a critical role for the reassessment of emerging market currencies which lead to a revaluation and a recalibration of their risk characteristics. Thus, less liquidity in the developed world affects severely emerging markets, leaving them to compete for scarce resources by offering cheaper currencies and more attractive asset valuations. This finding corroborates the work of Gravelle et al., (2006) who study currency and bond markets to identify changes in the structural transmission of shocks across countries.

In addition, we complement the existing literature on modelling dependencies and spillovers[5] with the use of copula functions. While there is extensive literature studying the co-movements between the international equity markets via copulas[6], there is no literature on using copulas to study the co-movements across markets of different asset types and risk factors. Additionally, we fill a gap in the literature since commodity, liquidity and credit channels' interactions with emerging market foreign exchanges have not been investigated in international literature prior. Our study is closely related with the works of Shleifer and Vishny (1997), Yuan (2005), Boyer et al., (2006), Carlin et al., (2007), Dungey et al., (2010), Boyer (2011), and Jotikasthira et al., (2012), who verify that market frictions break the link between asset price movements and economic fundamentals and accordingly, investors are not able to distinguish between selling based on liquidity shocks and selling based on fundamental shocks. We complement their work via proposing four contagion channels whose extreme adverse realisations spillover to emerging market foreign exchanges.

Particularly, Yang (2005) and Boyer et al., (2006) provide empirical evidence that market crashes are spread globally through asset holdings and wealth constraints of

[5]See e.g. Bubak et al., (2011), Sirr et al., (2011), Banti et al., (2012), Ahmad et al., (2012), Ulku and Demirci (2012), Tsai (2012), and Andreou et al., (2013).
[6]See also Ning (2010), Aloui et al., (2011), Kenourgios et al., (2011), Wang et al., (2013), and Aloui et al., (2013), for informative readings.

international investors. Shleifer and Vishny (1997), link asset market crashes with liquidity channels. We extend their work by observing four contagion channels whose extreme adverse realisations spillover to emerging currency markets. Jotikasthira et al. (2012) observe that uninformed investors suffering losses in an investment are “forced” to liquidate their positions, resembling to “fire sales”. We extend their work by providing strong evidence of asymmetric contagion which is caused by wealth constraints.

Furthermore, our study is related to the works of Wang et al., (2013), Ibragimov et al., (2013), Rossi and De Magistris (2013), Straetman and Candelon (2013), who observe tail risks in equity and foreign exchange markets. These authors document the existence of asymmetric dependence and highlight that emerging country exchange rates are more pronouncedly heavy tailed. We extend their works in emerging market foreign exchanges by identifying their relationship with several asset classes and risk factors. We also improve the understanding of risks in emerging currencies by providing novel evidence that accelerated decreases in commodity prices and in the spread of Banks’ Credit Default Swaps (BCDS) and prompt variations in volatility (VIX), provoke accelerated decreases and function as a barometer of emerging market currency fluctuations.

The remainder of the manuscript is organized as follows. Section 2 reviews the relevant literature. In Section 3 we set our theoretical framework and modelling strategy. We describe our dataset in Section 4 and report the empirical results in Section 5. Section 6 provides robustness checks. Section 7 discusses how shocks are propagated in the emerging currency market. Finally, section 8 presents the concluding remarks.

2. Literature Review

A. Theoretical Framework

According to the traditional portfolio theory, investors can improve the performance of their portfolios by allocating their investments into different asset classes (Markowitz, 1952). However, during turmoil periods, cross-market co-movements increase rendering traditional theory fruitless and advancing to contagion. As described by Forbes and Rigobon (2002), contagion occurs when there is a significant cross-asset or cross-market increase in comovement due to a shock. This extreme dependence is the aftermath of forced sales or "fire sales" by wealth-constrained investors (Yuan 2005; Boyer et al., 2006; and Jotikasthira et al., 2012). As these authors argue, uninformed rational investors are not able to distinguish between selling based on liquidity shocks and selling based on fundamental shocks. Thus, when investors suffer a large loss in an investment, they are forced to liquidate their positions in other investments, triggering cross-market portfolio rebalancing. We build on and extend these approaches to identify how shocks are propagated in emerging market currencies.

Severe financial conditions, like the recently experienced credit crunch, play an important role in driving economic activity in emerging economies (Akinci 2013). Global financial shocks increase uncertainty and fluctuations, and thus, the business climate deteriorates causing increased uncertainty for future growth prospects. Following Colin-Dufresne et al., (2001), Alexander and Kaeck, (2008), and Annaert et al. (2013), the higher the uncertainty the higher the volatility, and thus, the Volatility Index can be used as a proxy for business and credit market conditions. During periods of uncertainty, credit markets squeeze and liquidity abruptly dries up. Financial institutions suffer unanticipated outflow of deposits and experience funding and liquidity issues, and thus the spread in Banks' Credit Default Swaps increases (see also Jorion and Zhang, 2007; and Alexander and Kaeck, 2008; for the effects of credit events on credit default swaps). If funding and liquidity problems become a commonplace it is likely to have a recessionary effect on investment and consumption, and thus lead to lower expectations for growth in emerging markets and depress the prices of commodities (see also Arezki et al. 2014 for an overview on understanding commodity price fluctuations). Therefore investors shift funds from emerging stock markets causing unprecedented declines, resembling to domino effect (see also Markwat et al.,, 2009, who observe that crashes occur from local or regional shocks). All these channels described above, are factors that render an emerging market currency vulnerable to contagion.

Contagion refers to the risk that a shock in an asset leads to increased volatility and co-movements of other assets (see also Forbes and Rigobon, 2002; Boyson et al. 2010; and Allen et al. 2012). Indeed, the performance of global emerging market currencies shifted and altered contemporaneously during the peak of the financial crisis as never before in the recent history (see also Dias 2014; and Tolikas 2014 for informative readings on financial assets dramatic losses), providing anecdotal evidence for and resembling to contagion.

Our study builds on and extends a growing literature which emphasizes on the role of forced sales, liquidity spirals and hoarding, caused by the recent credit crisis, such as how the collapse of the subprime market acted as a channel of contagion and transferred risks to the stock market, Treasuries and corporate bond yields (Longstaff, 2010). This field has attracted the interest of a plethora of investigations. Jorion and Zhang (2006) examine the contagion channel between credit default swaps and stock markets. Boyer et al. (2006) propose a model where limits to arbitrage facilitate stock market crises to spread globally through asset holdings. Building on this approach, Aloui et al. (2011) examine the contagion effect and how cross market linkages increased during the recent global crisis between the US and BRIC stock markets. Boyson et al. (2010) and Jotikasthira et al. (2012) find strong evidence of contagion across hedge funds and that forced and fire sales in developed market funds perform as channels of risk and contagion on emerging market funds.

B. Empirical Framework

The literature on volatility transmission and contagion literally exploded since the thought-provoking studies by Allen and Gale (2000), Forbes and Rigobon (2002) and Barberis and Shleifer (2003). However, studies that aim at the interaction between foreign exchanges and stock markets are less frequent than those covering equity markets. Indeed, Bekaert and Harvey (1995, and 2000) identify cross border linkages of emerging stock markets. Chen et al. (2002) observe regional emerging stock markets interlinkages and spillovers in Latin American stock exchanges and Yang et al. (2006) find evidence of integration and co-movements at Central and Eastern European stock Indices.

Among the first researchers that examine spillovers between the developed U.S. stock market and foreign exchanges are Bartov and Bodar (1994), Karolyi and Stulz (1996), Bodard and Reding (1999). They find no evidence of volatility spillovers between the foreign exchange and the stock market returns. In particular, they observe that the value of dollar is negatively related to changes in US stock markets in the long run. Bodnar and Gentry (1993) investigate the Japanese and Canadian foreign exchange and stock markets and find no evidence of spillovers. On the other hand, Francis et al. (2002), attribute cross-currency differences in U.S. and European markets and observed that stock market return differentials are positively related to bilateral exchange rates.

Kearney and Patton (2000) employ a series of multivariate GARCH models on the members of the former European Monetary System (EMS) prior to their complete monetary unification and find that less volatile weekly data exhibit a significantly smaller tendency to transmit volatility compared to more volatile daily data. Menkhoff et al. (2012) study the curry trades and Ning (2010) observes significant symmetric upper and lower tail dependence between stock markets and foreign exchanges for the U.S., the U.K., Germany, Japan, and France. Ehrmann et al. (2011) study interactions between stock market and foreign exchange returns for the US and Eurozone and they find strong evidence of spillovers in the Eurozone but little effect from exchange rate changes on US stock market returns.

In order to overcome departures from normality and to conduct a study on the marginal behaviour and the dependence structure among the asset classes, without the imposition of any assumption in marginal distributions we apply copula functions. The copula theorem allows us to decompose the joint distributions into k marginal distributions, which characterise the single variables of interest (exchange rate volatility in our case), and a copula which describes the dependence between k variables. A copula function connects the marginal distributions to restore the joint distribution. In the extant literature, most studies observe and model co-movements focusing on stock indices with the use of copulas (Ning 2010; and Kenourgios et al. 2011) omitting to study foreign exchange volatility. Muller and Verschoor (2009) are among the very first to study the recent economic crisis, and identify significant falls in asset prices along with large and unexpected movements in foreign exchange rates. Garcia and Tsafack (2011) employ an Extreme Value Theory copula in a regime-switching model to highlight the joint extreme behavior of international equity and bond markets. Bonato et al., (2013) observe that currency-risk spillovers improve the forecasting ability of an international equity portfolio. Wang et al. (2013) develop a dependence switching copula model to describe the dependence structure between the stock and foreign exchange for six major industrial countries: France, Germany, Italy, Canada, Japan and the U.K.. They observe asymmetric tail dependence in a negative correlation regime and symmetric dependence in a positive correlation regime.

While there is extensive literature studying the co-movements between the international equity markets and studies on modelling the dependence structure between the exchange rates via copulas, there is no literature on using copulas to study the co-movements across different asset classes and exchange rates. To address the above mentioned concerns Patton (2006) uses normal (Gaussian) copula and the Symmetrised Joe-Clayton (SJC) copula to identify that the mark–dollar and yen–dollar exchange rates are more correlated when they are depreciating against the dollar than when they are appreciating. Moreover, the author observes asymmetries in the upper and lower tail dependences in the pre and post euro periods. Building on this approach Busetti and Harvey (2011), observe that a time-invariant copula is not appropriate and hence allow the parameters in a copula function to change over time. As investors are generally averse to downside risk, a copula should capture both the risk of joint downward movements of asset prices, and the diversification opportunities that assets offer. Rodriguez (2007) and Kenourgios et al. (2011) among others examine how contagion affects stock markets during the period of a financial crisis, while Okimoto (2008) investigates the co-movement of stock returns across countries.

On emerging markets, most of the available research focuses on the interaction and linkages between Asia and Central Eastern European markets: Phylaktis and Ravazzolo (2005) observe the Asia Pacific Region (Honk Kong, Malaysia, Phillipines, Singapore and Thailand) and find that there is bi-directional relationship and spillovers from the foreign exchange to the stock market returns in emerging market. Andreou et al. (2013) employ a VAR-GARCH framework and find bi-directional linkages between the stock and foreign exchange markets for Argentina, Brazil, Chile, Colombia, Mexico, Venezuela, India, Korea, Malaysia, Pakistan, Philipines, and Thailand.

Ulku and Demirci (2012) investigate the joint dynamics between emerging stock market and foreign exchange changes for eight European countries (Hungary, Poland, Turkey, Czech R., Russia, Ukraine, Romania and Croatia) and the MSCI Europe Index, and find that global developed and emerging stock market returns account for a large proportion of the comovement between stock markets and currencies. Bubak et al. (2011) study the dynamics of volatility transmission between Central European and the EUR/USD foreign exchange and report evidence of significant intra-regional volatility spillovers. They also observe that each CE currency has a different volatility transmission pattern vis a vis the EUR/USD and the EUR/CHF exchange rates, depending on the pre-2008 and the post -2008 periods.

3. Methodology

3.1 The advantages of using copula functions

In this study, we use the time-varying nature of the copula functions to examine the structural dependence between emerging currencies, emerging stock markets, commodities, the iTraxx Senior Financial Index (Banks' Credit Default Swaps or BCDS) and the Volatility Index. A copula is a multivariate cumulative distribution function whose marginal distributions are uniform on the interval [0,1]. Copulas are suitable to describe interrelations and to model dependence of several random variables. As described by Harvey (2010), copulas separate the marginal behaviour of variables from the dependence structure through the use of distribution functions. Thus, copula functions are more appropriate to adequately capture fat tails and higher moments. The advantages of using copulas are multi-fold. A copula is a function that connects the marginal distributions to restore the joint distribution and is very flexible in modelling dependence. By using copulas we are able to isolate the dependence structure from the marginal distributions. Consequently, copulas can be applied with any marginal distributions, and the marginal can be different from each other. Also, various copulas represent different dependence structure between variables. Following Aloui et al. (2011), copulas allow to separately model the marginal behavior and the dependence structure. This property gives us more options in model specification and estimation.

Furthermore, the copula function can directly model the tail dependence (see also Patton 2006). As described by Ning (2010) it is a succinct and exact representation of the dependencies between underlying variables, irrespective of their marginal distributions. More concretely, a copula function allows controlling for the marginals, to filter out marginal inequalities and influences in the dependence measure. As a result, the dependence measures based on a copula function are marginal free. Hence, one of the key properties of copulas is that they are invariant under increasing and continuous transformations. Moreover, the copula can easily model the asymmetric dependence by specifying different copulas. Another useful dependence measure defined by copulas is the tail dependence, which measures the probability that both variables are in their lower or upper joint tails.

A thorough review of copulas may be found in Patton and Sheppard (2009). Methodologically, we begin with capturing the linear measures of rank dependence with Kendall's τ and Spearman's ρ. Due to the drawbacks of linear measures, we then model the margins of the return series by fitting the appropriate ARMA-GARCH specifications to the actual data set and extract the standardised residuals, similar to Patton (2006), Kenourgios et al. (2011), and Aloui et al. (2011), in order to capture dependences and tail risks with three copula functions.

3.2 The Hypotheses

Following Acharya et al. (2011), a systemic financial crisis gives rise to a business-cycle recession, which weakens public finances and leads to a higher default risk (i.e. spreads in Banks' Credit Default Swaps accelerate[7]). Financial institutions that suffer unanticipated outflow of deposits and experience funding and liquidity issues in a wholesale market are forced to reduce their lending activity. If funding and liquidity problems become a commonplace in the banking sector, money supply will decrease as less credit will become

[7]Periods of higher (lower) global financial risk are typically associated with higher (lower) borrowing spreads and hence credit default swaps' prices tend to soar (decrease). See also Akinci (2013) for informative reading on this relationship.

available in the economy. Thus, liquidity abruptly dries up and credit risk soars (see also Jorion and Zhang (2007) for informative readings on the role of credit default swaps for portfolio rebalancing and contagion). This is likely to have a recessionary effect on investment, consumption, income, and thus leads to severe downturns in the commodity prices (see also Arezki et al. (2014) for informative readings on commodity price fluctuations[8]). Under these conditions, investors withdraw capital from risky investments and increase their exposures in safe assets such as government bonds issued by developed countries in a flight to quality. This signals net capital outflows in the emerging stock markets and point to a higher financial risk for investments in emerging countries. Thus, we formulate our first hypothesis:

Hypothesis 1 (Existence of contagion channels): Due to global shocks in liquidity, credit and growth constraints and in emerging stock markets, there is a significant cross-asset increase in the comovement and the dependence with emerging currencies, resembling to contagion.

Uninformed rational investors are not able to distinguish between selling based on liquidity shocks and selling based on fundamental shocks. Thus, when investors suffer a large loss in an investment, they are forced to liquidate their positions in the most vulnerable investments (i.e. emerging stock markets, according to Ibragimov et al. 2013) triggering cross-market portfolio rebalancing (see also Yuan 2005; Boyer et al., 2006; and Jotikasthira et al., 2012, for informative readings on forced sales and investor-induced contagion). Based on these we formulate our second hypothesis:

Hypothesis 2 (Investor – Induced Hypothesis and Asymmetric Contagion): The documented increase in the dependence (hypothesis 1) is triggered by cross-asset rebalancing, which is consistent with investor induced contagion. If the crisis spreads through cross-asset

[8]Higher financial risk leads to lower economic activity, and thus lower demand for commodities (i.e. prices tend to decline).

rebalances, then dependence should be asymmetrically higher during market downturns than in market upturns, pointing also to asymmetric contagion.

Local crashes and shocks in liquidity, credit and demand constraints spillover to emerging market currencies and thus evolve into global crashes, resembling to a domino pattern (see also Markwat et al., 2009). Based on this rationale we identify if emerging currency market contagion occurs as a domino effect.

Hypothesis 3 (Domino Effect Hypothesis): Shocks in the contagion channels evolve into global crashes and significantly increase the probability of more severe crashes, resembling to a domino effect.

Emerging market currencies have been among the worst performing assets over the last years. The Indian Rupee and the Brazilian Real have underperformed the US dollar by about 20%, similarly the Russian Ruble, the Mexican Peso and the South African Rand dropped over 10%. In line with these downdrafts, realized and implied volatility in emerging currencies doubled. Thus, we are searching if this is a cyclical downturn or a structural shift in the risk characteristics of these assets, based on Gravelle et al. (2006):

Hypothesis 4 (Structural Shift in Risk Determinants): If the structure of the simultaneous transmission of shocks to any pair of currencies is fundamentally altered by the crisis (i.e. post-crisis dependence is not the same with pre-crisis dependence), then there is a permanent change in the structural transmission of shocks to emerging market currencies, which implies a fundamental shift in their risk characteristics.

To formally test these implications, we employ copula functions to describe the distribution, tail coefficients and the dependence structure between the foreign exchange market, the financial market (local stock indices), the growth channel (the commodity market, represented by the S&P Goldman Sachs Commodity Index), the liquidity channel (i.e. Banks' Credit Default Swaps) and the credit channel represented by the Volatility

Index[9]. To address the relative importance of each component, we decompose co-movements to separate out the effects on the emerging markets exchange rates movements.

3.3 Marginal distributions

According to the copula theorem for a joint distribution function, the marginal distributions and the dependence structure can be separated as described by Patton (2006):

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

$$f_{xy}(x,y) = f_x(x) \cdot f_y(y) \cdot c(F_X(x), F_Y(y)) \tag{2}$$

The central result in copula theory states that any continuous N-dimensional cumulative distribution function F, evaluated at point $x = (x_1, \dots, x_N)^{(5)}$ can be represented as:

$$F(x) = C(F_1(x_1), \dots F_N(x_N)) \tag{3}$$

where C is a copula function and $F_i i = 1, \dots, N$ are the margins.

Copulas are very flexible in analysing co-movement and modelling dependence. Various copulas represent different dependence structure between variables, a property which provide us with more options in model specification and estimation.

Formally, a two – dimensional copula is a function $C : [0,1] \times [0,1] \rightarrow [0,1]$, such that

(i) $C(u,0) = C(0,v) = 0$ (C is grounded),

(ii) $C(u,1) = u$ and $C(1,v) = v$, (consistent with margins)

(iii) for any$u_1, u_2, v_1, v_2 \in [0,1]$with $u_1 \leq u_2$ *and* $v_1 \leq v_2$,

$C(u_2, v_2) + C(u_1, v_1) - C(u_1, v_2) - C(u_2, v_1) \geq 0$ (2-increasing)

Copulas are more informative measures of dependence between many variables than linear correlation, since they provide us with the degree and the structure of the dependence

[9]An increase in the Volatility Index indicates an increase in uncertainty and is associated with an increase in credit risk. Thus, following Colin-Dufresne et al. (2001), Alexander and Kaeck (2008), and Annaert et al. (2013), we use the VIX as a proxy for business and credit market conditions.

among financial assets. The copula function can directly model the tail dependence, while linear correlation does not provide information about it and for the symmetrical property of the co-movement. Hence, any copula function has a lower and an upper bound, C^{-} and C^{+}, which are known as the minimum and the maximum copula, respectively. For any point $(u, v) \in [0,1] \times [0,1]$ the copula must lie in the interval as follows:

$$C^{-}(u, v) \equiv \max(u + v - 1,0) \leq C(u, v) \leq \min(u, v) \equiv C^{+}(u, v).$$

As with standard distribution functions, copulas have associated densities which exist in the interior domain (Patton 2006) as given by:

$$c(u, v) = \frac{d^2 C(u,v)}{du dv} \tag{4}$$

The above permits the canonical representation of a bivariate density $f(u, v)$ as the product of the copula density and the density functions of the margins as given by:

$$f(u, v) = c\big(F_1(u), F_2(u)\big) f_1(u) f_2(v) \tag{5}$$

Equation (5) indicates how the product of two marginal distributions will fail to properly measure the joint distribution of two asset prices unless they are in fact independent. The dependence information captured by the copula density, $c\big(F_1(u), F_2(u)\big)$, is normalised to unity and shows that copula functions are an alternative dependence measure that is reliable when correlation is not.

Based on the work of Bollerslev (1986), Nelson (1991), and Patton (2006), we estimate the dependence described above, with a AR(*k*)-*t*-*GARCH*(p,q) model which detects conditional heteroscedastic errors. Thus, the daily return is expressed as:

$$R_t = \mu_t + \varepsilon_t = \mu_t + \sigma_t z_t,\ \ z_t \sim \text{iid}(0,1)$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2, \tag{6}$$

where μ_t denotes the conditional mean and σ_t^2 is the conditional variance with parameter restrictions ω > 0, α >0, β >0, and α+β >1. In order to verify that the marginal distributions are not normal, we employ the Jarque-Berra normality tests for each asset return. The order of the autoregressive terms is specified at a maximum of 10. Hence, given a time series y_t, the GARCH (1,1) model is described as:

$$y_{t=}c + \sigma_t\, z_t$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{7}$$

where z_t is an iid random variable with zero mean and variance of one. σ_t^2 is the conditional variable of return series at time t, with the same restrictions as noted in equation (6).

As noted by Kenourgios et al. (2011) and Aloui et al. (2011) copula functions can be used to characterise the dependence in the tails of the distribution. Upper and lower tail dependence coefficients can be used to measure and capture booms and crashes.

We assume that the variables of interest in our model are X and Y with marginal distribution functions F and G. Thus the coefficient of lower tail dependence λ_L is represented as:

$$\lambda_L = \lim_{t\to 0^+} \Pr[Y \leq G^{-1}(t)|\ X \leq F^{-1}\,(t)] \tag{8}$$

which quantifies the probability of observing a lower Y assuming that X is lower itself.

Similarly, the coefficient for the upper tail dependence λ_U is defined by:

$$\lambda_U = \lim_{t\to 1^+} \Pr[Y > G^{-1}(t)|\ X > F^{-1}\,(t)] \tag{9}$$

Thus, symmetry occurs when the lower tail dependence equals the upper tail dependence coefficient, otherwise there is asymmetry.

The Gaussian copula symmetry occurs when$\lambda_l = \lambda_u$.

As a result, the Gaussian normal copula can be expressed as:

$$C(u,v) = \Phi_\theta\big(\Phi^{-1}(u), \Phi^{-1}(v)\big) = \int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi\sqrt{1-\theta^2}} \exp(-\frac{s^2-2\theta st+t^2}{2(1-\theta^2)})\, dsdt \qquad (10)$$

where Φ_θ is the standard bivariate normal distribution with linear correlation coefficient θ restricted to the interval (-1,+1), and Φ represents the univariate standard normal distribution function.

Similarly, the Student-*t* copula can be defined as:

$$C(u,v) = \int_{-\infty}^{t_u^{-1}(u)} \int_{-\infty}^{t_u^{-1}(v)} \frac{1}{2\pi\sqrt{1-\theta^2}} \exp(1 + \frac{s^2-2\theta st+t^2}{u(1-\theta^2)})^{-\frac{u+2}{2}} dsdt \quad (11)$$

where ${t_u}^{-1}$(u) denotes the inverse of the cumulative distribution function of the standard univariate Student-t distribution with *u* degrees of freedom.

In the extant literature, it is well documented that the co-movement between assets usually have positive lower dependence (i.e. left tail dependence) depending on the strength of the volatility chasing effect. Hence, to capture the above dependence switching, this study follows Chen et al., (2009) and employs the flexible Joe-Clayton copula:

$$C_{JC}(u, v|\tau^U, \tau^L) = 1 - (1 - \{[1-(1-u)^\kappa]^{-\gamma} + [1-(1-v)^\kappa]^{-\gamma} - 1\}^{-1/\gamma})^{1/\kappa} \quad (12)$$

where $\kappa = 1/log_2(2 - \tau^U)$

$\gamma = -1/log_2(\tau^L)$

and $\tau^U \epsilon\ (0,1),\ \ \tau^L \epsilon\ (0,1)$ (13)

From equations (12) and (13) the Joe-Clayton copula has two parameters, τ^U *and* τ^L, which are measures of tail dependence. Following Patton (2006), the Joe-Clayton copula symmetry occurs when $\tau^U = \tau^L$.

Moreover, in order to compare the copula models we use the goodness of fit test based on a comparison of the distance between the estimated and the empirical copulas (Genest et al. 2009). Therefore:

$$C_n = \sqrt{n}(C_n - C_{\theta_n}) \quad (14)$$

The test statistic considered is based on Cramer-Von Mises criterion which indicates that large values of the statistic S_n lead to the rejection of the null hypothesis that the copula C belongs to a class C_0. In particular, the Cramer-Von Mises criterion can be defined as:

$$S_n = \int C_n(u)^2 dC_n(u) \quad (15)$$

3.4 Estimation method

In order to estimate the parameters of the copula, we use the Inference for the Margins approach which is modified appropriately for the use of this study. This approach imposes optimality criteria on the functions in the estimating equations rather than the estimators obtained from them. Thus, we define that the copula C has the dependence parameter as (θ) and the marginal parameters as ($\alpha_{1,}\alpha_{2,\ldots.}\ \alpha_d$). Hence, the estimators $\hat{\alpha}_i^{IFM}$of the parameter α_i are evaluated from the log-likelihood L_i of each margin in equations (8) – (12), so that: $\hat{\alpha}_i^{IFM} = argmax_{\alpha_i} L_i(\alpha_i)$. Consequently, $(\hat{\alpha}_1^{IFM},\ \hat{\alpha}_2^{IFM}, \ldots ,\ \hat{\alpha}_d^{IFM})$ is defined to be the MLE of the model parameters under conditions of independence. In the second step, the estimator $\hat{\theta}^{IFM}$ of the copula parameter θ^{IFM} is computed by maximizing the copula likelihood contribution, (i.e. L_C) with the marginal parameters α_i in the likelihood function[10] replaced by the first-stage estimators: $\hat{\alpha}_i^{IFM}$: $\hat{\theta}^{IFM} = argmax_\theta\, L_C\ (\widehat{\alpha}_1^{IFM},\ \hat{\alpha}_2^{IFM}, \ldots ,\ \hat{\alpha}_d^{IFM}, \theta)$. Thus, the two-stage IFM estimator $\hat{\alpha}_1^{IFM},\ \hat{\alpha}_2^{IFM}, \ldots ,\ \hat{\alpha}_d^{IFM}, \hat{\theta}^{IFM})$ solves:

$$\frac{\partial L_1}{\partial \alpha_1}, \frac{\partial L_2}{\partial \alpha_2}, \ldots, \frac{\partial L_d}{\partial \alpha_d}, \frac{\partial L}{\partial \theta} = 0 \tag{16}$$

Similar to the MLE, the IMF estimator is consistent and asymptotically normal under regular conditions. Patton (2006) and Ning (2010) propose the IMF method as often more efficient than the ML. They also argue that the IMF approach is more appropriate for models which involve a large number of parameters, similar to our approach.

4. Data description and descriptive statistics

Our data set employed from Bloomberg and Datastream and consist of five emerging market foreign exchanges vis-à-vis the U.S. Dollar: the Brazilian Real (BRE), the Russian Ruble (RUB), the Indian Rupee (INR), the Mexican Peso (MXN), and the South African Rand (ZAR). Also, we use data for the following five stock markets: Bovespa (Brazil), RTS

[10]The simultaneous maximisation of the log-likelihood function is available upon request.

(Russia), BSE Sensex (India), IPC (Mexico), and the Johannesburg Top 40 Index (South Africa, henceforth JSE Top 40). In addition, we use the following indices: (i) the S&P Goldman Sachs Commodity Index (S&P GSCI); (ii) iTraxx Senior Financials Index (Banks' Credit Default Swaps); and (iii) the Chicago Board Options Exchange Market Volatility Index (VIX) as a proxy of the business and credit climate. For our empirical analyses, we use a dataset of daily closing prices. The sample period is daily from March, 21, 2005 till June, 22, 2013 and excludes bank holidays. The nominal exchange rates are expressed as the number of units of national currency per US dollar. Also, all indexes are in U.S. dollars.

Figure 1 presents the movement of the emerging currencies from 2005 to 2013. The base currency is the U.S. Dollar and the area below zero represents an appreciation for the emerging currency (or depreciation of the U.S. Dollar against the emerging currency), while the area above zero represents devaluation of the emerging currency against the U.S. Dollar.

– Please Insert Figure 1 about here –

Table 1 depicts the summary statistics with the tests for normality. Over the sample period, the mean of the emerging currencies is negative (i.e. Brazilian Real: -0.0002) or fairly closed to zero, reflecting greater risk. Moreover, all emerging currencies are leptokurtic implying that the distribution departs from symmetry. These currencies experienced significant fluctuations over the sample period, as indicated by the range of variation in the standard deviation.

Stock and commodity (S&P GSCI) returns were less volatile, as suggested by the range of variation and the standard deviation. Indeed, daily percentage stock and commodity returns were positive during the sample period. Consistent with empirical evidence on skewness and kurtosis, returns are negatively skewed and leptokurtic, suggesting that big negative events in the stock and commodity markets are more likely than big positive events.

Furthermore, the density of returns is greater, since most observations are to the sample median. Therefore, the resulting distribution of returns is non-normal.

Changes in the volatility index VIX and in the Banks' Credit Default Swap spreads have a positive mean, suggesting that the expectations of market volatility and the spread of the BCDS were increasing over the sample period. Also, they underwent significant fluctuations over the sample period, as indicated by the range of variation in the standard deviation. The change in the volatility index and in the BCDS are also positively skewed and highly leptokurtic resulting in a non-normal distribution of values.

– Please Insert Table 1 about here –

5. Empirical Results

In order to compare the impact of the crisis on emerging market foreign exchanges, and to detect time-variation and structural breaks, we analyse dependence and tail dependence separately for the period from March 2005 to August 2007 (Pre-crisis Period), for the period from August 2007 to September 2009 (Crisis Period), and for the period from September 2009 to June 2013 (Post-crisis Period). We follow the assumption made by Ozkan and Unsal (2012), that the global financial turmoil started in August 2007 and we find that the underlying return and volatility series behave differently across these three sample periods.

5.1 Linear correlations

We start by interpreting the results of the rank correlation coefficients as applied to the emerging market foreign exchanges. Our estimation results are displayed in Table 2. We observe that for the overall sample period the Kendall's tau and Spearman's ro statistics are positive, implying positive dependence between emerging market foreign exchanges, domestic stock market indices and the growth channel (S&P GSCI commodity index). This finding indicates that the probability of concordance is significantly higher than the probability of discordance. Additionally, our findings imply that the Brazilian Real and the Russian Ruble appear to be particularly susceptible to changes in the growth channel, indicating that the response of these currencies is significantly quicker to changes and fluctuations in commodity prices. In particular, for the Brazilian Real and the Russian Ruble, the strongest dependence is observed with the S&P GSCI. Positive dependence indicates that the booming demand for commodities has underpinned these currencies. Contrarily, the Indian Rupee, the Mexican Peso and the South African Rand are more susceptible to changes in the domestic stock markets, than with changes in the growth channel.

During the crisis period, the results suggest a strong and sudden increase in the cross-asset synchronization of fluctuations and volatilities. The dependence structure changes and increases substantially - Kendall's τ and Spearman's ρ rise to higher levels for all considered pairs-, implying that shocks in the domestic stock markets and the growth channel lead to increased crash likelihood in emerging currencies. For instance, during the crisis period the dependence between the Brazilian Real and the growth channels increases to 0.136 for the Kendall's τ and 0.171 for the Spearman's ρ respectively. This finding indicates that these currencies display a significant reversal, following shocks to financial and commodity markets.

Adversely, in the post crisis period the dependence structure weakens- Kendall's τ and Spearman's ρ decrease for all considered pairs-, reflecting a structural break or a regime shift that divides the behaviour of the emerging currencies. Notably, in the post-crisis period emerging currencies share stronger comovement with the domestic stock markets, while in the crisis and the pre-crisis period they share a stronger comovement with the growth channel (i.e. S&P GSCI).

On the other hand, the results reveal a very different picture for the dependence between emerging currencies, the Volatility Index and the Banks' Credit Default Swaps. In particular, for the overall sample, both Kendall's tau and Spearman's ro statistics are negative between emerging market foreign exchanges and the Volatility Index, and Banks' Credit Default Swaps, implying that there is no co-movement. By contrast, during the crisis period the dependence becomes positive indicating that during high volatility periods, where uncertainty increases, liquidity abruptly dries up and credit markets squeeze, changes in the Volatility Index and in the spread of Banks' Credit Default Swaps are followed by changes in emerging market currencies. Indeed, during the financial crisis the Volatility index and BCDS increased substantially while fluctuations soared in emerging market currencies. This relationship also indicates that the Volatility Index and the spread of the BCDS, function as a barometer of emerging currency movements and can be used as a hedging proxy for investments in emerging market currencies during volatile periods.

The results for the post-crisis period suggest that emerging market exchange rates become more pronouncedly heavy-tailed in downward moves than in upward moves. This finding indicates statistically decreases in the tail indices and structural breaks to these exchange rates due to the recent financial crisis that correspond to the increase in the likelihood of large fluctuations. As a result, on the post crisis period, emerging market foreign exchanges are more susceptible to financial crisis and speculative attacks. The increased likelihood of extreme joint losses suggests a higher than normal Value at Risk. The above results are intuitively in line to some extent with the findings of Bubak et al. (2011), Sirr et al. (2011), Ulku and Demirci (2012), Aloui et al. (2011 and 2013), and Andreou et al. (2013), who document directional spillovers between financial assets (i.e. stock and foreign exchange markets).

– Please Insert Table 2 about here –

Table 3 reports the estimated AR(k)-t-GARCH(p,q) model for each asset return series. We experiment on AR and GARCH terms of up to 2 lags and we find that the asset returns experience a short memory with a significant AR (2). Also, GARCH (2,2) is capable to capture the conditional heteroscedasticity. The *p*-values of the Jarque-Bera test are less than 0.0001 indicating that there is not normality. Furthermore, the degrees of freedom of the *t* distribution are all small, ranging from 2 to 7, implying that the error terms are not normal and indicating the existence of contemporaneous extreme co-movements and tail dependences in emerging market currencies. Furthermore, the significance of the degrees of freedom suggests that the Gaussian copula is not sufficient in modelling the dependence between the four contagion channels and the emerging currencies.

– Please Insert Table 3 about here –

5.2 Copula dependence

We report the estimation results of the dependence parameters for each pair of emerging market currency in Table 4 and Figures 2 and 4. The copula parameter estimates are significant for all emerging market currencies, when the Gaussian, Student – *t* and Joe-Clayton copulas are applied. The pairwise dependences are significantly positive for the domestic stock markets and the growth channel. Thus, positive (or negative) changes in stock market and commodity returns are followed by positive (or negative) changes in the emerging market currencies. Again, the growth channel shares the strongest dependence with the Brazilian Real and the Russian Ruble, while the domestic stock markets have the strongest co-movement with the Indian Rupee, the Mexican Peso and the South African Rand. By contrast, as expected, there is a negative dependence structure between emerging currencies, the changes in the Volatility Index and the changes in the Banks' Credit Default Swaps.

– Please Insert Table 4 about here –

– Please Insert Figure 2 and Figure 4 about here -

During the financial meltdown, the results reported in Table 5 and Figure 3 suggest strong and sudden increases in the cross market synchronization, consistent with the notion of contagion. This verifies that, given an extreme negative value in the four variables, there is a significantly positive probability to observe increased fluctuations and high volatility in emerging currencies at the same period. Indeed, the dependence during the crisis period increases substantially for all considered emerging market currencies, supporting hypothesis 1. Consequently, the dynamics of volatility transmission is not structurally stable and constant over time. During severe financial conditions dependence increases, shocks and fluctuations in the domestic stock markets, commodity, credit and liquidity variables perform as contagion channels whose extreme adverse realisations are associated with a slump of the emerging market currencies. This finding sheds new light on the propagation of large negative cross-asset returns. Furthermore, the presence of risk spillovers among asset classes increases portfolio risk and magnifies the volatility of the expected returns in emerging market currencies.

Since the relations between the variables and the crash probabilities are stronger in times of turmoil, this can be interpreted as excessive dependence. Thus, we observe extreme value dependence over and above what one would expect from economic fundamentals, pointing to contagion. Fluctuations and elevated volatility strengthens informational contents of the contagion channels and raises uncertainty. Consequently, investors demand higher risk premium in order to invest in the emerging market currencies, triggering deep sell offs. The increase in cross-asset co-movements diminishes rapidly diversification opportunities and renders traditional portfolio theory fruitless. These results are intuitively in line with Kodres and Pritsker (2002), Yuan (2005), Boyer at. al. (2006), and Jotikasthira et al., (2012), who provide empirical evidence for contagion among asset holdings.

After finding empirical evidence in support of the contagion hypothesis, we investigate how the financial crisis was spread through the four contagion channels which represent asset holdings of investors. Table 5 and Figures 3 and 5 show that the tail dependence when these markets are booming (upper and right tail) is not the same as that when markets are crashing (lower and left tail). Consequently, since lower tail dependence increases, co-movements increase under severe financial conditions causing asymmetry between upper and lower tails. These findings support the investor-induced contagion (i.e. hypothesis 2) which is sourced by cross-asset rebalancing and assumes asymmetric tail dependence and asymmetric contagion during high volatility periods. These results corroborate the works of Longin and Solnik (2001), Kyle and Xiong, (2001), Ang and Chen (2002), and Boyer at. al., (2006) who document asymmetric investor induced contagion, which is stronger during market downturns for international financial markets.

In addition, the results imply that accelerated decreases in the stock market, in the growth channel (commodity index) and large variations in credit (i.e. Volatility Index) and liquidity (BCDS) markets lead to accelerated decreases and increased fluctuations in emerging market foreign exchanges. During the crisis period the stronger relationship is observed with the Volatility Index. This finding confirms that the Volatility Index captures fluctuations and adverse behaviour of the emerging market currencies and thus its derivative (i.e. Volatility Futures Index) can be used as a hedging proxy, complimenting the works of Ning (2010), and Campbell et al.,, (2010) who study the dependence structure in the foreign exchange markets and global currency hedging strategies, respectively.

– Please Insert Table 5 about here –

– Please Insert Figure 3 and Figure 5 about here –

5.3 Goodness of fit test

Following Genest et al. (2009) we compare the distance of the goodness-of-fit test to select the most appropriate copula function. For this test, the null hypothesis states that the estimated copula provides the best fit to the data for the p-values that are higher than the conventional significance level (equations 14 and 15). The results presented in Table 6 and Figure 6 show that for all considered pairs, the Joe-Clayton Copula yields the smallest distance for the conducted goodness-of-fit test, indicating that the Gaussian and the *t*- copulas are not sufficient in modelling the tail dependence. The *t*- Copula provides an approximation which is much better than the normal copula, but still underestimates the tail of losses considered. As described above, the Joe-Clayton copula distribution allows for heavy-tails (i.e. high frequency of heavy losses) which help to overcome the “normality” assumption of the Gaussian copula which underestimates the probability of large losses. Moreover, the model assumes asymmetric tail dependence in the distribution, implying that upper and lower tail dependence is not equal supporting hypothesis 2. These results are in line with the findings of Patton (2006), Aloui et al. (2013), and Wang et al. (2013) who employed copula functions to examine dependence between international stocks and currencies.

– Please Insert Table 6 about here –

– Please Insert Figure 6 about here –

5.4 The domino pattern

As discussed in the previous sections, shocks in the commodity prices, large variations in Banks’ Credit Default Swaps and in the Volatility Index significantly increase the comovement and spillover to emerging market currencies. Indeed, the significance of the crash variables suggests that currencies depreciated heavily, following the developments of these variables. This is consistent with the notion of the domino pattern, supporting hypothesis 3 (see also Markwat et al., 2009 for informative readings). Particularly, a domino effect exists when past occurrences of local crashes evolve via regional crashes into global crashes. Furthermore, on the post crisis period emerging market foreign exchanges become more pronouncedly heavy-tailed (i.e. l_{λ} is higher compared with the pre-crisis period) in downward moves, increasing the likelihood for more explicit currency crashes. This result is also consistent with the domino effect which is present when past occurrences of local crashes increase the probability of more severe crashes.

5.5 How the credit crunch altered the structural transmission of emerging currencies

To capture upper and lower tail risks, we compute the tail dependence coefficients implied by the Joe-Clayton Copula which provides the ability to better capture the fat tails. As discussed in the methodology section, λ_l (λu) quantify the dependence structure between the four contagion variables and emerging currencies, when they are in extremely small (large) values. It is evident from Table 7 that the dependence structure is significant, indicating that shocks (booms) in the contagion channels spillover to the emerging market currencies. Furthermore, the results imply that the structure of the dependence is asymmetric, i.e. lower tail and upper tail dependence is not exactly equal $\lambda_l \neq \lambda$u. Under symmetry, this difference would be equal or fairly closed to zero. Comparing the dependence before and after the financial meltdown, the Joe-Clayton copula results suggest that in the pre and post crisis period the corresponding appreciation is not experienced with the similar magnitude, given that emerging currencies were depreciated heavily during the recent credit crisis. Indeed, in the post-crisis period, the smooth of the upper tail dependence (λ_u) drops systematically, rendering dynamics of conditional dependence, and the dependence between structures asymmetric, consistent with asymmetric investor induced contagion and supporting the argument that the credit crisis caused a structural shift in the transmission of shocks in these currencies (i.e. hypothesis 4). This finding compliments the work of Gravelle et al.,

(2006) who study currency and bond markets to identify changes in the structural transmission of shocks across countries. Notably, with respect to the difference between the pre-and post-crisis periods, spillovers seem to attenuate in the long-term during the post-crisis period. This finding affects the pricing of emerging market currencies in the post-crisis period for safety-first investors, since risk-averse investors favour investments with low dependence which hedge portfolio risks.

Moreover, the empirical results reported in Table 7 document significant and symmetric lower tail dependence during the financial crisis, indicating an increased likelihood of extreme joint losses. Indeed, λ_l is between 0.48 and 0.51 for all considered emerging currencies. This result, also confirms that the four contagion variables are more dependent with emerging currencies at the time of crashing than booming. These findings have important risk and asset pricing implications, since left tail dependence indicates the potential of simultaneous large losses and higher probability of extreme co-movements and contagion. Tail dependence implies higher than normal joint risk, a tendency to experience concurrent extreme shocks, and thus, higher than normal Value-at-Risk. Furthermore, the existence of joint tail risk alters the pricing of the emerging currencies over time. These results extend the works of Wang et al., (2013) and Ibragimov et al., (2013) who study tail dependencies for emerging market foreign exchanges.

Interestingly, the results suggest that the relevance of information flow from the four contagion variables might have changed suddenly during the financial meltdown. Indeed, with respect to the difference between the pre- and post-crisis periods, lower tail dependence increases substantially, implying that shocks in the four contagion channels lead to increased crash likelihood in the emerging market currencies. Hence, compared to the period before the crisis, uncertainty has been transmitted in a disproportionate way across the emerging market foreign exchanges (hypothesis 4). Additionally, this implies that emerging market currencies become more pronouncedly heavy-tailed in downward moves than in upward moves. Furthermore, this finding indicates a structural break due to the recent financial crisis that corresponds to the increase in the likelihood of large fluctuations, resembling to a domino effect. As described by Markwat et al., (2009), a domino effect is present when past occurrences of local crashes evolve via regional crashes into global crashes. As a result, on the post crisis period, emerging market foreign exchanges are more susceptible to financial crisis and speculative attacks. We hence conclude that the Joe-Clayton copula function is able to explain the shifts in emerging market currency movements during the credit crisis.

– Please Insert Table 7 about here –

5.6 Economic implications: The symptoms of acute liquidity withdrawal

In the previous sections we described how the dependence structure of the emerging market currencies changes from the pre-crisis to the crisis and then to the post-crisis period. We document strong and sudden increase in cross-asset synchronization, consistent with the notion of investor induced contagion which is sourced by cross-asset rebalancing. These findings imply that emerging currencies display a significant reversal, following shocks to financial, commodity, liquidity and credit channels. The increase in cross-asset dependence diminishes rapidly diversification opportunities and renders traditional portfolio theory fruitless. Furthermore, the presence of risk spillovers among these asset classes, increases portfolio risk and magnifies the volatility of the expected returns in emerging market currencies.

In the post-crisis period we observe the existence of a structural shift in the transmission of shocks that divides the behaviour of these currencies. Emerging market exchange rates become more pronouncedly heavy-tailed in downward moves than in upward moves. As a result, on the post crisis period, emerging currencies are more susceptible to financial crisis and speculative attacks. These findings affect the pricing of emerging market currencies in the post-crisis period for safety-first investors, since risk-averse investors favour investments with low dependence which hedge portfolio risks. Emerging currencies benefited the most from the macroeconomic tailwinds that boosted growth in the pre-crisis period. However, it is evident that the credit crunch was the catalyst for the change in the structure of the transmission of shocks to emerging currencies and more concretely played a critical role for the reassessment of emerging market currencies which lead to a revaluation and a recalibration of their risk characteristics, indicating that this multi-year underperformance in emerging assets is not a cyclical downturn. Thus, less liquidity in the developed world affects severely emerging markets, leaving them to compete for scarce resources by offering cheaper currencies and more attractive asset valuations.

6. Robustness checks

In order to check the sensitivity of our results, we employ an alternative GARCH model and the bivariate hit and joint hit tests proposed by Patton (2006) and Ning (2010). These tests approve the suitability of our proposed approach for modelling the relationships between emerging market currencies, local stock markets, growth, liquidity and credit channels. In particular: (i) we employ a non-linear extension of GARCH, the Exponential GARCH (2,2) model proposed by Nelson (1991) and (ii) we divide the support of the copula into seven regions, so that regions one and two represent the lower and upper joint 10% tails for each variable and measure the probability of all variables. Regions three and four correspond to moderately large up and down days. Region five denote days where the exchange rates were in the middle 50% of their distributions. Regions six and seven correspond to the extremely asymmetric days. Additionally, we perform a joint hit test which represents the regions that are not covered by regions one to seven.

6.1 Alternative GARCH approach

The EGARCH model reveals and is suitable for testing asymmetries, volatility clustering and leptokurtosis. Indeed, we employ the skewed generalised Student-*t* EGARCH distribution to capture the skewness effects in our sample. This checking procedure is important as it allows us to confirm the suitability of our proposed approach for modelling the relationships between emerging market currencies and the four contagion channels.

Table 8 presents the results for the dependence coefficients with respect to the EGARCH (2,2) model. For the overall sample period we observe that there is significant positive dependence and comovement with the domestic stock markets and the growth channel supporting our proposed approach. Again, the strongest relationship for the Brazilian Real and the Russian Ruble is observed between the emerging currencies and the growth channel (i.e. commodity index), implying that developments in the commodity prices lead the movement of these currencies. By contrast, the Indian Rupee, the Mexican Peso, and the South African Rand have the strongest dependence with the domestic stock markets. Positive dependence indicates that a change in the contagion channels is followed by a significant change in the emerging currencies.

However, the pattern of comovement over the crisis period differs from the whole sample. Consistent with our initial results, during the crisis period the dependence increases substantially, implying that negative shocks in the stock market and the commodity index have a stronger effect on the currencies. The strongest relationship during the crisis period stands with the Volatility Index. Hence, during high volatility periods, where uncertainty increases and credit markets squeeze, changes in the Volatility Index are followed by changes in the emerging currencies.

– Please Insert Table 8 about here –

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6.2 Hit test

In order to evaluate the copula models we employ the hit tests, as proposed by Patton (2006). The results in Table 9 verify if the models are well-specified in all regions simultaneously (i.e. joint hit test). The *p*-values are higher than 0.05 implying that the models are well-specified. We also employed the following tests[11]: (i) if the models are well specified in the joint lower and upper 10% regions; (ii) if the models are well specified in moderately up and down days; (iii) if the models are well specified when all exchange rates are in the middle 50% of their distributions; (iv) if the models are well specified during extremely asymmetric days. The results suggest that the Joe-Clayton copula is the most appropriate model to capture fluctuations and volatility spikes in emerging market currencies. Indeed, the *p* – value is higher than 0.05 for all considered currencies in all regions. By contrast, the Gaussian and *t*-Copulas are rejected by the hit test is some regions, for some currency pairs.

– Please Insert Table 9 about here –

7. How shocks are propagated in the emerging currency markets

As discussed by Liang (2013) and Allen and Carletti (2013), the recent financial meltdown demonstrates vividly that there are many channels through which seemingly small losses, spillover and transfer risk on the broader financial system. Building on and extending this approach, we identify four key contagion variables which can amplify shocks and lead to instability and whose extreme adverse realisations are associated with a slump of emerging market foreign exchanges. These variables represent liquidity, credit, growth constraints and the local emerging markets. Under severe financial conditions, funding and liquidity problems become a commonplace in the banking sector, increasing the spread on the Banks'

[11]More results for all hit tests are available upon request by the authors.

Credit Default Swaps. Money supply decreases as less credit is available in the economy. Thus, liquidity abruptly dries up, credit risk soars leading to increased uncertainty and fluctuations in the markets, and thus the Volatility Index accelerates. This is likely to have a recessionary effect on investment, consumption, income, and thus leads to severe downturns in the commodity prices (i.e. the growth channel). As a result, investors withdraw capital from risky investments and increase their exposures in safe assets such as government bonds issued by developed countries, in a flight to quality. This signals net capital outflows in the emerging stock markets and point to a decrease in the creditworthiness of government bonds issued by an emerging country. Consequently, when liquidity dries up, default probabilities accelerate, credit risk intensifies, growth expectations deteriorate, emerging stock markets crash and hence, shocks in these variables spillover and transfer risks to emerging market currencies.

8. Conclusion

In this study, we model and examine conditional and tail dependences for the most rapidly developed emerging market foreign exchanges. We use four alternative measures to investigate the transmission mechanism and explore how shocks propagate emerging currencies. In contrast to the majority of the existing empirical literature we employ Gaussian, Joe-Clayton and t-Copula functions in order to identify spillovers across markets of different types. We also analyse the extent to which shocks in stock, commodity, liquidity and credit channels are transmitted to fluctuations in emerging currencies. In response to the questions raised in the introduction, the empirical results provide strong evidence that cross-asset linkages during periods of high volatility are over and above any economic fundamentals. We capture synchronically the behaviour of emerging currencies and the interactions with other assets and risk factors. Thus, we provide empirical evidence that large adverse shocks in the four channels described above, spill over to emerging market currencies, resembling to investor induced contagion and supporting the hypothesis that the recent credit crisis was spread through these contagion channels and cross-asset portfolio constraints. Our explicit distinction between the four contagion channels and our modelling for the evolution of these crashes sheds new light on the propagation of large negative cross-asset returns.

Furthermore, we find that during the crisis period, there is a significant genuine increase in the cross-asset asymmetric synchronisation and the dependence with emerging currencies, advancing to asymmetric contagion. Additionally, we observe that past occurrences of local crashes evolve via regional crashes into global crashes, indicating that the crisis was spread in a domino fashion into emerging market currencies. Our empirical results document that during the financial crisis dependence among assets increased significantly, resembling to extreme tail dependence. The dependence in the extremes is generated by the idiosyncratic contagion channels, which are the outcome of several shocks and wealth constraints. The significance of the tail dependence implies that these asset classes tend to experience concurrent extreme shocks. Moreover, we observe that accelerated decreases and large variations in the domestic stock markets, in the growth (i.e. commodities), liquidity (BCDS) and credit channels (i.e. VIX) lead to accelerated decreases and increased fluctuations in the emerging market foreign exchanges. Finally, we document that in the post-crisis period, emerging market foreign exchanges are more susceptible to financial crises and speculative attacks, implying the existence of a structural shift in the transmission of shocks that divides the behaviour of these currencies. The importance that external shocks and liquidity hoarding have in shaping the movement of these emerging currencies is amplified and shows that the symptoms of liquidity withdrawal in the developed markets lead to a revaluation and a recalibration of the risk characteristics of emerging currencies.

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Appendix A: Variables Definition

Variable	Definition
Brazilian Real	The local currency of Brazil.
Russian Ruble	The local currency of Russia.
Indian Rupee	The local currency of India.
Mexican Peso	The local currency of Mexico.
South African Rand	The local currency of South Africa.
Bovespa Stock Index	The Bovespa stock exchange is located in Sao Paulo, Brazil. It is one of the thirteen largest stock exchanges in the world. The Index is the benchmark indicator for the 381 companies traded in Bovespa.
RTS Stock Index	The Index consists of 50 Russian stocks with the largest capitalisation and is traded on the Moscow Exchange, Russia.
BSE Sensex Stock Index	The index consists of the 30 largest and most actively traded stocks listed on Bombay Stock Exchange, India.
IPC Stock Index	Is the main benchmark for the Mexican Stock Exchange. It is made up of a balanced weighted selection of shares based on market capitalisation.
JSE Top 40 Stock Index	It is the first equally weighted index and the benchmark index for the Johannesburg Stock Exchange. It consists of the 40 largest stocks by market capitalization.
S&P GSCI	The S&P GSCI (formerly the Goldman Sachs Commodity Index) is a benchmark index for investments in the commodity market and a measure of commodity performance over time. It is a tradable index which is based on the Chicago Mercantile Exchange. The index comprises 24 commodities from all commodity sectors. The wide range of constituent commodities provides the S&P GSCI with a high level of diversification, across subsectors and within each subsector.
iTraxx Senior Financials (BCDS)	The iTraxx Senior Financials Index comprises the 25 largest banks, based on their capitalization. It is a benchmark Index which offers protection in case a bank defaults and represents the credit conditions in the financial sector. Credit Default Swaps are derivative contracts that allow investors to protect themselves against a deterioration of credit quality and even a default. An increase in the price of Banks' Credit Default Swaps indicates deterioration in liquidity and credit market conditions
Volatility Index	The volatility index (VIX) is a popular measure of the implied volatility of the S&P 500 index options for the Chicago Board Options Exchange Market Volatility Index and represents a measure of the market's expectation of stock market volatility.

Appendix B. Linear Correlations

It is very common with the Copula functions to employ also various other measures of dependence (see also Patton 2007, Ning 2010, Aloui et al. 2011). Our returns are not assumed to have an elliptical distribution, thus Pearson's linear correlation is an inaccurate and misleading measure. In order to measure the association between two continuous random variables X and Y denoted $(x_{1,}y_1)$ and $(x_{2,}y_2)$ we assume that the pairs are concordant if $(x_1\text{-}x_2)$ has the same sign as $(y_1\text{-}y_2)$. Hence, the pairs are concordant if:

$$(x_1\text{-}x_2)\ (y_1\text{-}y_2) > 0 \qquad (b1)$$

and discordant if:

$$(x_1\text{-}x_2)\ (y_1\text{-}y_2) > 0 \qquad (b2)$$

In this study we develop Kendall's t and Spearman's ρ to measure the proportion of the concordant pairs. Both methods represent rank correlations (i.e. are non parametric measures of dependence), do not depend on marginal distributions and are the difference between the probability of the concordance and the probability of the discordance, so that:

$$\tau\alpha\upsilon\ (\mathrm{X},\mathrm{Y}) = P[(X_1 - X_2)(Y_1 - Y_2) > 0] - P(X_1 - X_2)(Y_1 - Y_2) < 0] \qquad (b3)$$

for $\tau\alpha\upsilon \in [-1,1]$.

The higher the $\tau\alpha\upsilon$ value, the stronger is the dependence. Thus:

Similarly, we estimate the Spearman's *ρho* rank correlation by:

$$\rho = 1 - \frac{6D}{n(n^2-1)} \qquad (b4)$$

Where n is the paired observations $(x_{i,}y_i)$ and D is the sum of the squared differences between the ranks.

Figures

Figure 1. Performance of Emerging Market Currencies versus the U.S. Dollar

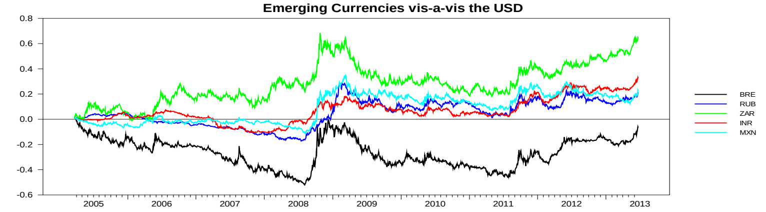
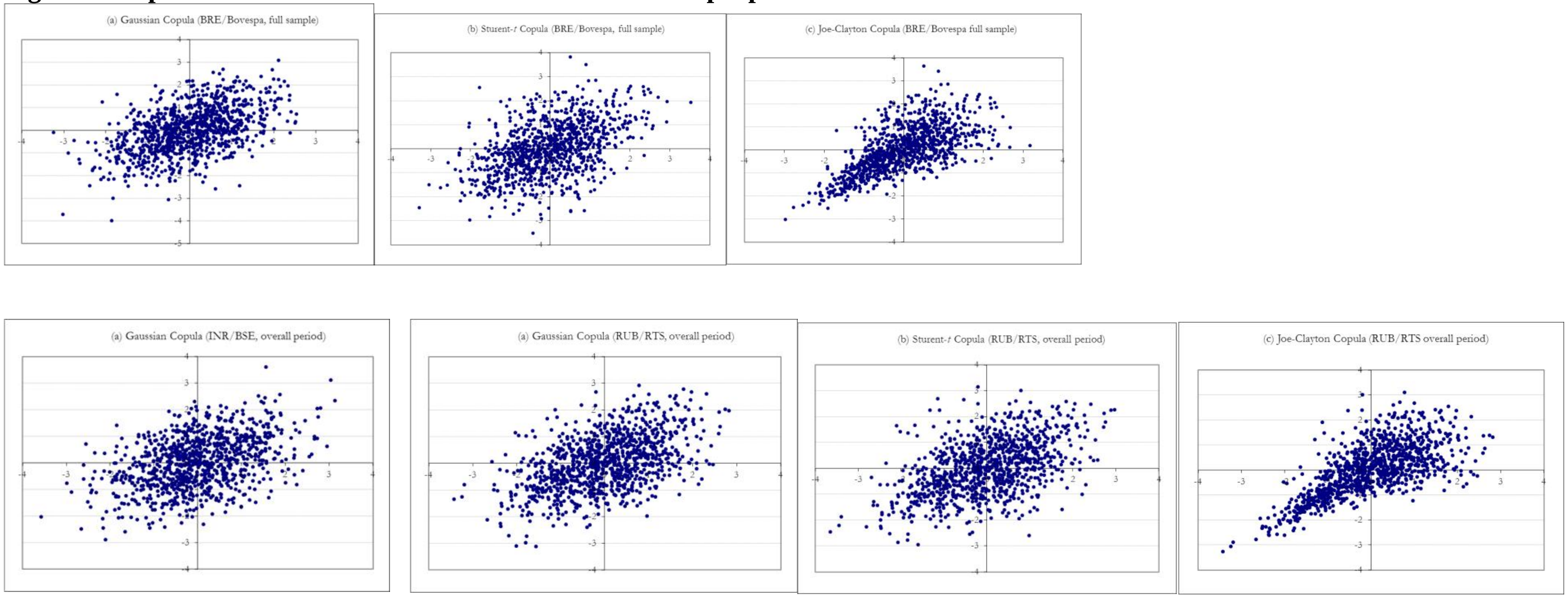


Figure 2. Copula Functions Observations for the overall sample period.



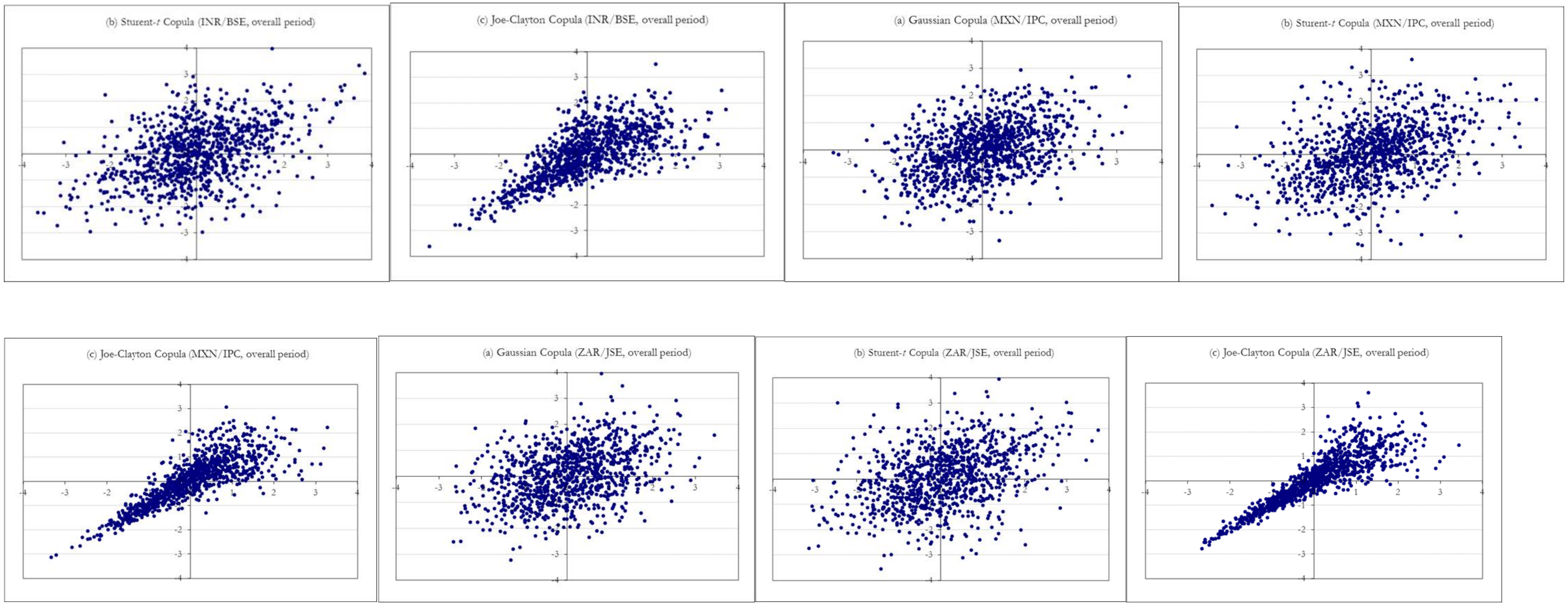
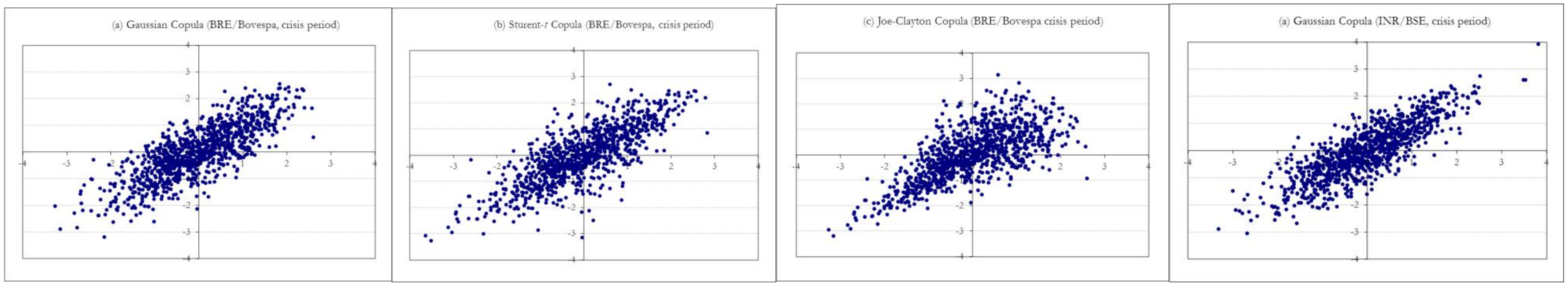
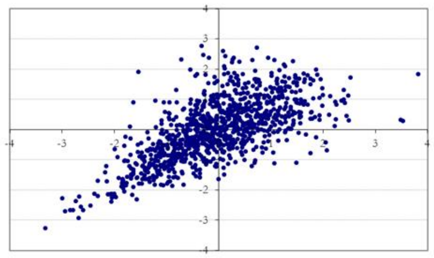
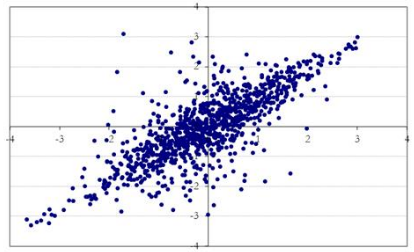
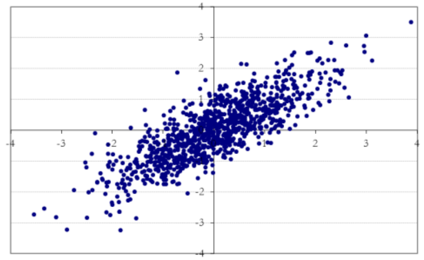


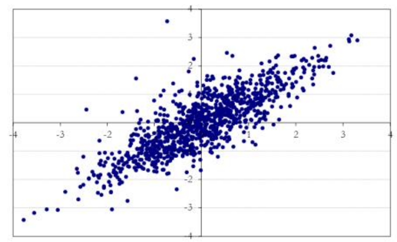
Figure 3. Copula Functions Observations for the crisis period.

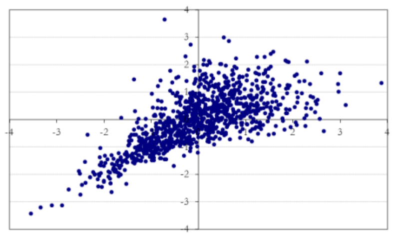


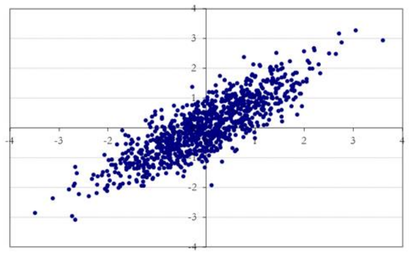

(c) Joe-Clayton Copula (INR/BSE, crisis period)

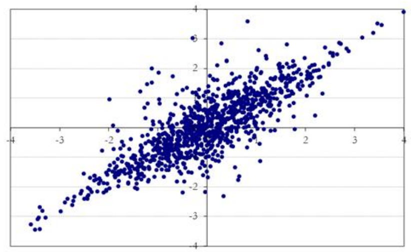

(b) Sturent-*t* Copula (INR/BSE, crisis period)

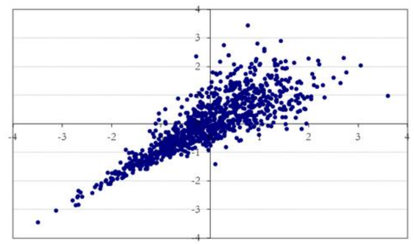

(a) Gaussian Copula (RUB/RTS, crisis period)

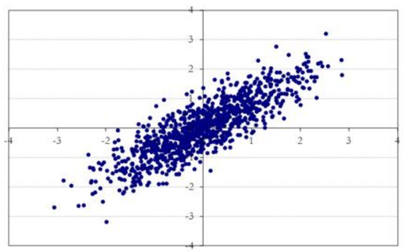

(b) Sturent-*t* Copula (RUB/RTS, crisis period)

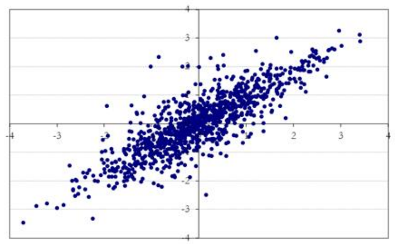

(c) Joe-Clayton Copula (RUB/RTS crisis period)


(a) Gaussian Copula (MXN/IPC, crisisl period)


(b) Sturent-*t* Copula (MXN/IPC, crisisl period)


(c) Joe-Clayton Copula (MXN/IPC, crisis period)


(a) Gaussian Copula (ZAR/JSE, crisis period)


(b) Sturent-*t* Copula (ZAR/JSE, crisis period)

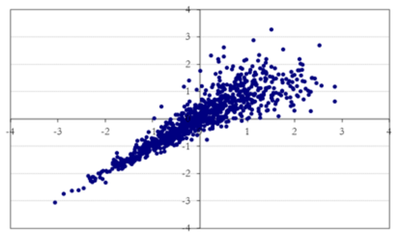

(c) Joe-Clayton Copula (ZAR/JSE, crisis period)

Figure 4. Copula Densities for the overall sample period.

Gaussian Copula Densities, BRE/S&P GSCI. Student –*t* Copula Densities, BRE/S&P GSCI. Joe-Clayton Copula Densities, BRE/S&P GSCI.

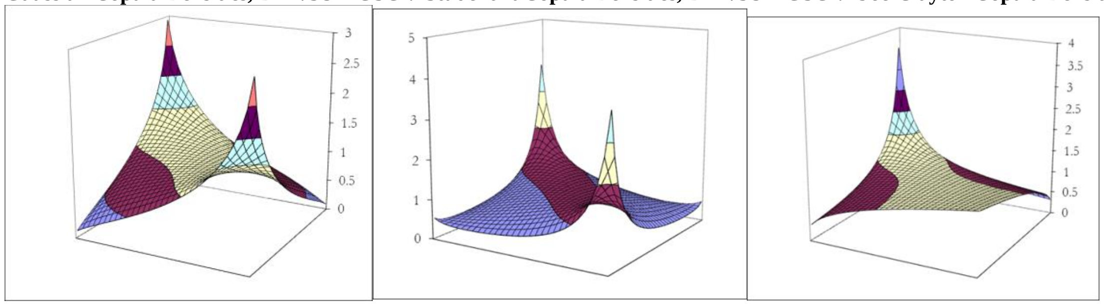


Figure 5. Copula Densities for the crisis period.

Gaussian Copula Densities, BRE/S&P GSCI. Student –*t* Copula Densities, BRE/S&P GSCI. Joe-Clayton Copula Densities, BRE/S&P GSCI.

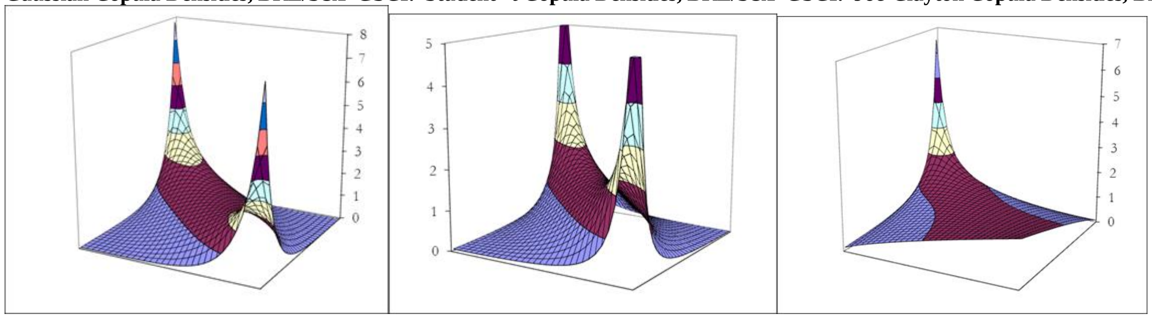
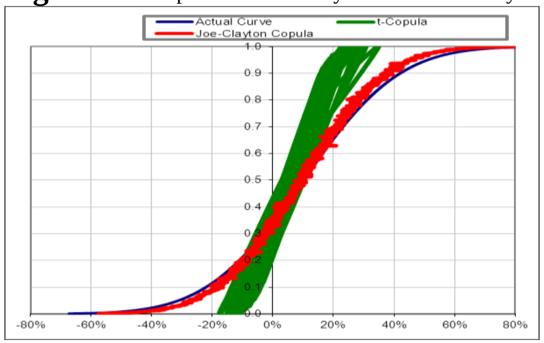


Figure 6. Comparison between Symmetrized Joe-Clayton (red line) and *t*- Copula (green line) for the model that fits best the data (blue line).



Tables

Table 1
Summary Statistics.

Variables	Obs	Mean	Median	Max	Min	Std	Skew	Kurt	JB	Prob
Brazilian Real	2153	-0.0002	1.94	2.73	1.53	0.24	0.0435	20.77	38703	0.0000
Russian Ruble	2153	0.0024	12.11	36.34	23.13	2.67	0.4873	9.25	7776	0.0000
Indian Rupee	2153	0.0072	45.70	59.57	39.25	4.38	0.0207	4.29	1655	0.0000
Mexican Peso	2153	0.0009	12.11	15.41	9.89	1.16	0.6730	11.42	11861	0.0000
South African Rand	2153	0.0019	7.40	11.37	5.96	0.98	0.4929	11.56	12086	0.0000
Bovespa	2153	5.09	29056	44672	9496	9535	-0.3175	3.34	1037	0.0000
RTS	2153	0.2691	1508	2487	498	430	-0.5233	5.84	3168	0.0000
BSE Sensex	2153	0.0776	338	531	140	86.29	-0.0691	5.82	1337	0.0000
ICP	2153	0.7812	2600	3680	1054	638	-0.3997	3.77	1337	0.0000
JSE Top 40	2153	10.42	25257	37599	11242	5858	-0.1728	1.97	361	0.0000
S&P GSCI	2153	-0.8204	5.15	10898	3116	1417	-0.2271	4.53	1865	0.0000
VIX	2153	0.0021	18.36	80	9.89	10.47	0.5491	17.11	26389	0.0000
BCDS	2153	106	101	353	7.0	81.98	0.5518	2.50	131	0.0000

Note. This table presents summary statistics, the Jarque-Bera test statistic, and the *p*-values associated to the Jarque-Bera test statistic of the change in emerging market foreign exchanges, the local stock markets, the commodity market index (S&P GSCI), the Volatility Index, and the Banks' Credit Default Swaps (iTraxx Senior Financials). All variables are expressed in U.S. dollar terms and are defined in Appendix A. The sample period is 22/03/2005 – 21/06/2013 and contains a total of 2153 daily observations.

Table 2
Correlation estimates of exchange rates and the four contagion channels.

	Variables	Overall Sample		Pre-Crisis Period		Crisis Period		Post Crisis Period	
		Kendall-τ	**Spearman-ρ**	**Kendall -τ**	**Spearman-ρ**	**Kendall-τ**	**Spearman-ρ**	**Kendall-τ**	**Spearman-ρ**
Brazilian Real	**Bovespa**	0.102	0.114	0.071	0.076	0.127	0.155	0.090	0.096
	S&P GSCI	0.104	0.119	0.073	0.088	0.136	0.171	0.087	0.094
	VIX	-0.052	-0.043	-0.109	-0.101	0.072	0.094	0.014	0.019
	BCDS	-0.079	-0.060	-0.121	-0.113	0.065	0.082	0.009	0.016
Russian Ruble	**RTS**	0.129	0.166	0.103	0.117	0.201	0.274	0.083	0.098
	S&P GSCI	0.165	0.179	0.127	0.154	0.214	0.303	0.079	0.087
	VIX	-0.135	-0.110	-0.262	-0.227	0.078	0.094	0.011	0.015
	BCDS	-0.146	-0.129	-0.274	-0.250	0.061	0.079	0.002	0.004
Indian Rupee	**BSE Sensex**	0.134	0.168	0.121	0.135	0.217	0.311	0.059	0.072
	S&P GSCI	0.097	0.139	0.089	0.126	0.185	0.214	0.041	0.060
	VIX	-0.142	-0.127	-0.268	-0.231	0.086	0.105	0.008	0.012
	BCDS	-0.157	-0.163	-0.270	-0.246	0.062	0.090	0.002	0.005
Mexican Peso	**IPC**	0.154	0.186	0.127	0.135	0.239	0.336	0.114	0.128
	S&P GSCI	0.070	0.084	0.071	0.080	0.159	0.203	0.039	0.050
	VIX	-0.117	-0.102	-0.146	-0.131	0.058	0.074	0.003	0.005
	BCDS	-0.121	-0.109	-0.152	-0.140	0.052	0.071	-0.005	-0.001
South African Rand	**JSE Top 40**	0.148	0.173	0.125	0.139	0.237	0.276	0.142	0.159
	S&P GSCI	0.072	0.089	0.051	0.063	0.119	0.138	0.067	0.082
	VIX	-0.131	-0.116	-0.197	-0.142	0.074	0.091	0.002	0.003
	BCDS	-0.137	-0.122	-0.176	-0.138	0.060	0.073	0.004	0.007

Note: This table summarizes Kendall's τ and Spearman's ρ rank correlation estimates for each exchange rate return pair. The sample is divided in four periods, the overall period and three sub-periods, in order to show the effects of the recent credit crunch. Positive significance implies co-movements and dependence. All variables are expressed in U.S. dollar terms and are defined in Appendix A. The sample period is 22/03/2005 – 21/06/2013and contains a total of 2153 daily observations.

Table 3
Estimation of marginal models.

Variables	Intercept	AR1	AR2	ARCH1	ARCH2	GARCH1	GARCH2	JB test	DoF
Brazilian Real	0.005 (0.012)	0.042 (0.021)	0.042 (0.018)	0.053 (0.014)	0.053 (0.140)	0.922 (0.013)	0.922 (0.013)	0.0000	7
Russian Ruble	0.004 (0.011)	0.043 (0.021)	0.043 (0.018)	0.057 (0.014)	0.057 (0.014)	0.937 (0.012)	0.937 (0.012)	0.0000	5
Indian Rupee	0.003 (0.106)	0.043 (0.021)	0.043 (0.018)	0.041 (0.010)	0.041 (0.011)	0.928 (0.013)	0.092 (0.013)	0.0000	4
Mexican Peso	0.002 (0.102)	0.046 (0.021)	0.046 (0.018)	0.069 (0.014)	0.069 (0.014)	0.958 (0.010)	0.958 (0.010)	0.0000	7
South African Rand	0.003 (0.104)	0.047 (0.020)	0.047 (0.019)	0.068 (0.013)	0.067 (0.013)	0.959 (0.010)	0.958 (0.010)	0.0000	2
Bovespa	0.049 (0.013)	0.050 (0.023)	0.050 (0.019)	0.037 (0.007)	0.037 (0.007)	0.940 (0.011)	0.940 (0.010)	0.0000	6
RTS	0.061 (0.013)	0.051 (0.023)	0.051 (0.019)	0.043 (0.008)	0.043 (0.080)	0.958 (0.010)	0.957 (0.010)	0.0000	5
BSE Sensex	0.052 (0.013)	0.051 (0.023)	0.051 (0.019)	0.060 (0.013)	0.060 (0.013)	0.953 (0.010)	0.953 (0.010)	0.0000	4
IPC	0.073 (0.014)	0.053 (0.023)	0.053 (0.019)	0.073 (0.013)	0.072 (0.013)	0.963 (0.010)	0.963 (0.010)	0.0000	6
JSE Top 40	0.075 (0.014)	0.056 (0.023)	0.056 (0.019)	0.082 (0.013)	0.082 (0.013)	0.972 (0.010)	0.972 (0.009)	0.0000	2
S&P GSCI	0.048 (0.013)	0.051 (0.023)	0.050 (0.192)	0.042 (0.008)	0.041 (0.078)	0.962 (0.010)	0.961 (0.010)	0.0000	7
VIX	-0.012 (0.022)	0.043 (0.020)	0.043 (0.185)	0.036 (0.007)	0.036 (0.006)	0.914 (0.013)	0.914 (0.013)	0.0000	7
BCDS	-0.012 (0.022)	0.041 (0.020)	0.040 (0.019)	0.035 (0.006)	0.034 (0.006)	0.912 (0.014)	0.912 (0.013)	0.0000	6

Note: This table presents the estimation of the AR(k)-t-GARCH (p,q) models for each foreign exchange return, with significant level at 5%. In parentheses are the standard errors. DoF refers to the degrees of freedom of T distributions. All variables are expressed in U.S. dollar terms and are defined in Appendix A. The sample period is 22/03/2005 – 21/06/2013and contains a total of 2153 daily observations.

Table 4
Estimates of copula dependence parameters, overall sample**.**

	Variables	Gaussian	Standard Error	Student-t	Standard Error	Joe-Clayton	Standard Error
Brazilian Real	**Bovespa**	0.223	0.020*	0.229	0.019*	0.256	0.022*
	S&P GSCI	0.232	0.020*	0.240	0.021*	0.270	0.024*
	VIX	-0.006	0.010	-0.004	0.010	-0.003	0.010
	BCDS	-0.005	0.010	-0.002	0.010	-0.002	0.010
Russian Ruble	**RTS**	0.192	0.017	0.196	0.017	0.247	0.021*
	S&P GSCI	0.214	0.020*	0.203	0.018	0.263	0.023*
	VIX	-0.007	0.010	-0.005	0.010	-0.003	0.010
	BCDS	-0.006	0.010	-0.004	0.010	-0.003	0.010
Indian Rupee	**BSE Sensex**	0.211	0.020*	0.215	0.019*	0.251	0.022*
	S&P GSCI	0.127	0.012	0.199	0.017	0.228	0.019*
	VIX	-0.008	0.010	-0.006	0.010	-0.006	0.010
	BCDS	-0.008	0.010	-0.005	0.010	-0.004	0.010
Mexican Peso	**IPC**	0.263	0.023*	0.270	0.024*	0.273	0.024*
	S&P GSCI	0.140	0.013	0.148	0.013	0.216	0.019*
	VIX	-0.009	0.010	-0.007	0.010	-0.006	0.010
	BCDS	-0.007	0.010	-0.003	0.010	-0.001	0.010
South African Rand	**JSE Top 40**	0.239	0.021*	0.242	0.022*	0.282	0.025*
	S&P GSCI	0.222	0.019*	0.227	0.019*	0.237	0.020*
	VIX	-0.006	0.010	-0.004	0.010	-0.004	0.010
	BCDS	-0.008	0.010	-0.007	0.010	-0.006	0.010

Note: This table presents the estimated copula dependence parameters for the Gaussian, Student-*t* and Joe-Clayton copula functions for the overall sample period. The symbol* indicates significance of coefficients at the 5% level. All variables are expressed in U.S. dollar terms and are defined in Appendix A. The sample period is 22/03/2005 – 21/06/2013and contains a total of 2153 daily observations.

Table 5
Estimates of copula dependence parameters, crisis period (08/2007 – 09/2009).

	Variables	Gaussian	Standard Error	Student-t	Standard Error	Joe-Clayton	Standard Error
Brazilian Real	**Bovespa**	0.227	0.020*	0.253	0.022*	0.311	0.030*
	S&P GSCI	0.241	0.021*	0.267	0.023*	0.320	0.031*
	VIX	0.222	0.020*	0.227	0.020*	0.317	0.030*
	BCDS	0.218	0.019*	0.221	0.020*	0.293	0.027*
Russian Ruble	**RTS**	0.219	0.019*	0.229	0.020*	0.314	0.030*
	S&P GSCI	0.223	0.020*	0.238	0.020*	0.328	0.031*
	VIX	0.218	0.019*	0.226	0.020*	0.327	0.031*
	BCDS	0.216	0.019*	0.224	0.010*	0.259	0.022*
Indian Rupee	**BSE Sensex**	0.224	0.020*	0.231	0.020*	0.308	0.029*
	S&P GSCI	0.219	0.019*	0.226	0.020*	0.281	0.026*
	VIX	0.237	0.020*	0.244	0.021*	0.295	0.027*
	BCDS	0.218	0.019*	0.222	0.020*	0.247	0.021*
Mexican Peso	**IPC**	0.278	0.024*	0.302	0.028*	0.293	0.028*
	S&P GSCI	0.246	0.021*	0.247	0.021*	0.275	0.026*
	VIX	0.280	0.020*	0.309	0.029*	0.304	0.029*
	BCDS	0.218	0.019*	0.226	0.020*	0.260	0.023*
South African Rand	**JSE Top 40**	0.250	0.022*	0.295	0.028*	0.342	0.033*
	S&P GSCI	0.234	0.020*	0.242	0.021*	0.256	0.022*
	VIX	0.243	0.021*	0.266	0.023*	0.305	0.029*
	BCDS	0.221	0.019*	0.232	0.020*	0.249	0.021*

Note: This table presents the estimated copula dependence parameters for the Gaussian, Student-*t* and Joe-Clayton copula functions for the crisis period. The symbol * indicates significance of coefficients at the 5% level. All variables are expressed in U.S. dollar terms and are defined in Appendix A. The sample period is 22/03/2005 – 21/06/2013and contains a total of 2153 daily observations.

Table 6
Distance between empirical and estimated copulas.

	Variables	Gaussian	P-Value	Student-t	P-Value	Joe - Clayton	P-Value
Brazilian Real	**Bovespa**	0.042	0.041	0.038	0.039	0.031	0.035
	S&P GSCI	0.043	0.041	0.041	0.040	0.028	0.033
	VIX	0.049	0.047	0.047	0.045	0.041	0.040
	BCDS	0.049	0.047	0.047	0.045	0.042	0.041
Russian Ruble	**RTS**	0.044	0.043	0.040	0.039	0.033	0.036
	S&P GSCI	0.045	0.044	0.040	0.039	0.034	0.037
	VIX	0.048	0.047	0.042	0.041	0.036	0.038
	BCDS	0.049	0.047	0.043	0.042	0.037	0.039
Indian Rupee	**BSE Sensex**	0.050	0.049	0.042	0.041	0.032	0.035
	S&P GSCI	0.052	0.051*	0.048	0.047	0.036	0.038
	VIX	0.052	0.051*	0.047	0.045	0.035	0.038
	BCDS	0.054	0.052*	0.050	0.049	0.049	0.047
Mexican Peso	**IPC**	0.040	0.038	0.034	0.037	0.017	0.024
	S&P GSCI	0.049	0.047	0.048	0.047	0.045	0.044
	VIX	0.048	0.047	0.039	0.040	0.021	0.027
	BCDS	0.053	0.052*	0.045	0.044	0.043	0.042
South African Rand	**JSE Top 40**	0.040	0.038	0.031	0.035	0.014	0.023
	S&P GSCI	0.053	0.051*	0.050	0.049	0.050	0.049
	VIX	0.050	0.049	0.045	0.044	0.046	0.045
	BCDS	0.055	0.054*	0.052	0.051*	0.050	0.049

Note: This table presents the distance between the empirical and the estimated copulas according to Cramer-Von Mises statistic. The symbol * indicates the rejection of the copula model at the 5% level. All variables are expressed in U.S. dollar terms and are defined in Appendix A. The sample period is 22/03/2005 – 21/06/2013and contains a total of 2153 daily observations.

Table 7
Tail dependence coefficients.

	Variables	Overall Sample		Pre-Crisis Period		Crisis Period		Post-Crisis Period	
		λ_l	λ_u	λ_l	λ_u	λ_l	λ_u	λ_l	λ_u
Brazilian Real	**Bovespa**	0.039	0.044	0.030	0.054	0.051	0.036	0.047	0.049
	S&P GSCI	0.042	0.046	0.039	0.057	0.050	0.025	0.046	0.031
	VIX	0.038	0.019	0.026	0.012	0.051	0.067	0.053	0.024
	BCDS	0.029	0.012	0.023	0.008	0.049	0.028	0.036	0.021
Russian Ruble	**RTS**	0.042	0.045	0.037	0.059	0.051	0.039	0.042	0.044
	S&P GSCI	0.046	0.049	0.042	0.067	0.052	0.037	0.045	0.036
	VIX	0.037	0.018	0.029	0.008	0.050	0.053	0.041	0.021
	BCDS	0.032	0.014	0.026	0.005	0.050	0.034	0.046	0.025
Indian Rupee	**BSE Sensex**	0.043	0.045	0.037	0.053	0.051	0.036	0.040	0.042
	S&P GSCI	0.034	0.030	0.031	0.038	0.049	0.022	0.032	0.030
	VIX	0.042	0.016	0.039	0.009	0.051	0.055	0.043	0.019
	BCDS	0.029	0.010	0.021	0.004	0.048	0.030	0.030	0.013
Mexican Peso	**IPC**	0.049	0.048	0.046	0.055	0.050	0.041	0.049	0.045
	S&P GSCI	0.026	0.022	0.023	0.029	0.048	0.018	0.024	0.028
	VIX	0.048	0.037	0.045	0.013	0.051	0.058	0.047	0.034
	BCDS	0.023	0.012	0.018	0.003	0.048	0.013	0.029	0.026
South African Rand	**JSE Top 40**	0.050	0.051	0.048	0.061	0.051	0.043	0.049	0.053
	S&P GSCI	0.028	0.030	0.024	0.032	0.048	0.027	0.026	0.029
	VIX	0.039	0.018	0.030	0.010	0.049	0.040	0.033	0.035
	BCDS	0.023	0.011	0.013	0.003	0.048	0.016	0.031	0.024

Note: This table presents the estimates of the lower and upper tail dependence parameters documented from the best fitting copula model for each currency pair. The sample is divided into four categories: overall, pre-crisis, crisis and post-crisis periods in order to provide a better description for the effects of the credit crunch and the change in the dependence in the pre and post-crisis periods. All variables are expressed in U.S. dollar terms and are defined in Appendix A. The sample period is 22/03/2005 – 21/06/2013and contains a total of 2153 daily observations.

Table 8
Estimates of Copula Dependence Coefficients with EGARCH specification.

	Variables	EGARCH – overall period		EGARCH – crisis period	
		Student – *t* Copula	**Joe-Clayton Copula**	**Student – *t* Copula**	**Joe-Clayton Copula**
Brazilian Real	**Bovespa**	0.143*	0.167*	0.159*	0.186*
	S&P GSCI	0.152*	0.189*	0.203*	0.238*
	VIX	-0.005	-0.002	0.205*	0.243*
	BCDS	-0.011	-0.009	0.118*	0.125*
Russian	**RTS**	0.124*	0.131*	0.170*	0.192*
Ruble	**S&P GSCI**	0.146*	0.173	0.202*	0.245*
	VIX	-0.007	-0.005	0.206*	0.248*
	BCDS	-0.010	-0.009	0.124*	0.146*
Indian Rupee	**BSE**	0.138*	0.159	0.153*	0.180*
	S&P GSCI	0.120*	0.126*	0.138*	0.155*
	VIX	-0.007	-0.003	0.162*	0.189*
	BCDS	-0.009	-0.008	0.126*	0.132*
Mexican Peso	**IPC**	0.157*	0.184*	0.196*	0.243*
	S&P GSCI	0.113*	0.117*	0.128*	0.135*
	VIX	-0.013	-0.008	0.201*	0.284*
	BCDS	-0.017	-0.015	0.120*	0.122*
South African	**JSE Top 40**	0.161*	0.193*	0.219*	0.256*
Rand	**S&P GSCI**	0.118*	0.124*	0.135*	0.141*
	VIX	-0.013	-0.010	0.220*	0.267*
	BCDS	-0.029	-0.018	0.112*	0.116*

Note: This table presents the estimated Student-*t* and Joe-Clayton dependence coefficients using the alternative EGARCH specification. * indicates significance at the 5% level. The sample is divided in two categories: overall and crisis period in order to provide a better description for the effects of the credit crunch. All variables are expressed in U.S. dollar terms and are defined in Appendix A. The sample period is 22/03/2005 – 21/06/2013and contains a total of 2153 daily observations.

Table 9
Hit Test.

	Variables	Overall period			Crisis period		
		Gaussian copula	*t*-copula	Joe-Clayton Copula	Gaussian copula	*t*-copula	Joe-Clayton Copula
Brazilian Real	**Bovespa**	0.0830	0.2528	0.3593	0.1434	0.2859	0.3750
	S&P GSCI	0.0872	0.2930	0.4580	0.1683	0.3657	0.4116
	VIX	0.0532	0.0766	0.1023	0.1095	0.3503	0.4059
	BCDS	0.0511	0.0604	0.0938	0.0857	0.1594	0.1993
Russian Ruble	**RTS**	0.0923	0.3550	0.5076	0.1684	0.4039	0.5285
	S&P GSCI	0.0980	0.3879	0.5892	0.1958	0.4768	0.6020
	VIX	0.0529	0.0720	0.1031	0.0909	0.3059	0.5003
	BCDS	0.0508	0.0624	0.7553	0.0753	0.1108	0.1387
Indian Rupee	**BSE**	0.0821	0.3081	0.5020	0.1395	0.5391	0.6188
	S&P GSCI	0.0804	0.3005	0.3756	0.1108	0.3886	0.4205
	VIX	0.0523	0.0671	0.8990	0.9536	0.5049	0.6009
	BCDS	0.0511	0.0603	0.7014	0.7422	0.1052	0.1305
Mexican Peso	**IPC**	0.1420	0.4412	0.6520	0.1953	0.6952	0.8536
	S&P GSCI	0.0528	0.1582	0.2057	0.1004	0.2209	0.2995
	VIX	0.0746	0.2540	0.3588	0.1582	0.3958	0.5098
	BCDS	0.0503	0.0627	0.0890	0.0829	0.1053	0.1759
South African Rand	**JSE Top 40**	0.1552	0.7399	0.8009	0.2040	0.8938	0.9953
	S&P GSCI	0.0842	0.2427	0.3005	0.1105	0.2774	0.3590
	VIX	0.0506	0.6360	0.8523	0.1302	0.2039	0.5663
	BCDS	0.0501	0.5104	0.5949	0.08472	0.1053	0.1884

Note: This Table presents the *p*-values of the joint hit test. The sample is divided in two categories: overall and crisis period in order to provide a better description for the effects of the credit crunch. A number over 0.05implies that the model is well – specified in the region. All variables are expressed in U.S. dollar terms and are defined in Appendix A. The sample period is 22/03/2005 – 21/06/2013and contains a total of 2153 daily observations.