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Modeling Interaction between Carry Trade and Stock Markets: GARCH-EVT-COPULA

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Abstract — We **examine the interaction between Carry Trade strategy (CT) and stock markets during crash and boom periods. We apply a GARCH-EVT-SJC Copula model to study and compare the dependence structure; we find an important dependence during the crashes against a relatively weak relationship during period of booms. Our results confirm the presence of downside risk in CT, and therefore, suggest the inappropriate of the strategy to be an alternative asset class that could improve portfolio performance, as mentioned by [1].**

Keywords — Carry Trade ; Stock markets ; extreme dependence ;Extreme Value Theory ; Copulas.

I. INTRODUCTION:

The CT has a disreputable reputation in the financial press as well as the academic literature. This strategy which involves borrowing money in a currency with low interest rates in order to purchase assets in a currency with higher interest rates presents currently an easy route to investment wealth.

Our article focuses on the dependence structure between the stock markets and the CT market during periods of booms and crashes. Indeed, previous studies involved analysis on profitability and volatility transmission between the two markets but have not provided analysis on the level and dependence, specially, in times of extremes moves in share prices. These studies are based on Spillover effects (e.g [2],[3], and [4]) and regime switching [5] to accentuate the dynamism of this relationship that depends on market conditions. Thus, to the best of our knowledge, there is no debate on the extreme dependence structure, that is, the literature does not provide evidence for the relation between the CT and stock markets during expansion and crash markets.

To this end, we apply Conditional Extreme Value Theory (EVT-GARCH) and time-varying copula approach, using this combination, we are able to study structure dependence by focusing directly on tails and, therefore, could give us better estimations.

The remainder of the paper is organized as follows: the section 2 deals with the literature review on the dependence between CT and financial markets. In section 3, we discuss the methodology through which we define the GARCH-EVT-COPULA model. Finally, the presentation and discussion of the empirical results will last.

II. LITERATURE REVIEW

There exists a vast literature that focuses on the relationship between the CT and the financial markets. These studies show a high level of dependence because of capital flows generated by the strategy. Reference [5] postulate that this interaction is regime-dependent. Reference [6] and [7] show that the CT has generated low returns during stock market crash in 2008. References [8] demonstrate the role of yen CT in augmented the debt in yen currency and the appreciation of financial assets out of Japan.

In the same line, the authors of [2] analyze the relationship between daily returns of currency CT and US stock market for the period January 1995- September 2010. Using an EGARCH model, the results show a unidirectional relationship between the two markets, more precisely, it was observed a spillover effects from the stock market returns to CT returns, however CT returns does not have any spillover effect on the stock market returns.

Recently, [3] examine the information linkage between CT and Asiatic markets using a CCC-GARCH (1,1)-t. The model shows a strong information transmission between the two markets. Reference [9] find that the most popular CT currencies are more affected by the US equity markets than volatility level.

According to [10], the CT contributed to speculations in financial markets from 1999 to 2009; the increases of share prices in Central and Eastern Europe markets is explained by the increasing in using CT which was lucrative during that period.

In global, those studies highlight the importance of studying the dependence between the two markets. According to many authors, this link become stronger by moving from ordinary periods to periods whose occurrence frequency is low (booms; crashes).

Our research tends to examine and compare the features of this relation during market booms and crashes by applying a GARCH-EVT-SJC COPULA.

III. METHOTODOLY

A. Conditional EVT:

Extreme Value Theory (EVT) concerns the asymptotic behavior of extreme observations of a random variable. It is a static tool used to consider probabilities associated with extreme and rare events. The conditional EVT was introduced for the first time by [11] and is implemented in two stages.

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- Fit the GARCH model in order to get the standardized residuals *i.i.d*
- Apply the tools of EVT to the *i.i.d* residuals

1) GARCH asymmetric:

Let R_t be the dynamic of average returns represented by the following AR process:

$$R_t = u_t+\varepsilon_t = u_t +\sqrt{h_t}Z_t$$

Where $u_t = a_0 + \sum_{i=1}^{S} a_i R_{t-i}$

- a_0 is a constant,
- a_i are the parameters,
- R_{t-i} are the lags of returns,
- ε_t are the residuals that follow a Generalized Error Distribution,
- $Z_t = \varepsilon_t /\sqrt{h_t}$ is a normalized residual ; and,
- h_t is a conditional variance of ε_t that is supposed to follow one of three GARCH (p,q) asymmetric (*EGARCH, TGARCH and PGARCH*).

2) Estimation of parameters using Peak Over Threshold method

This stage consists of applying the tools of EVT to standardized residuals obtained from AR-GARCH. There are two methods of the EVT allowing the identification of extreme events: the method of Maximum Bolck (BM) and Peak Over Threshold (POT).

The BM models divide the time series into non-overlapping periods of same size and consider only the maximum values in each period. Those methods are fitted using generalized extreme value distribution (GEV). A more modern approach which is usually used in the literature is the POT models. This model considers extreme values of the sample that exceed a certain threshod *u* and is fitted by a GPD (e.g, [12] and [13]). More precisely, they show that for a sufficiently large threshold *u*, the probability distribution function of these extremes observations could be approximately a GPD. The GPD is defined as:

$$G_{\xi\psi}(y) = 1 - \left(1 + \frac{\xi y}{\psi}\right)^{\frac{-1}{\xi}}, si\ \xi \neq 0$$
$$= 1 - e^{\frac{-y}{\psi}}, si\ \xi = 0$$

- ξ is the shape parameter
- ψ is the scale parameter.

Thus, we refer to the Mean Excess Plot (MEP) which is a tool widely used in EVT practices that permit to judge about an appropriate threshold.

B. Copula approach:

1) Definition

A copula is a multivariate function with uniform marginal distribution; it reflects dependence structure between two random variables. According to the theorem of [14], let *F* be the distribution of the variable *X*, *G* is the distribution of the variable *Y* and *H* is the joint distribution of (*X*,*Y*). When *F* and *G* are continuous, there exists a single copula *C*;

$$H(X,Y)=C(u,v),$$

Where;

- *u= F(X)*
- *v= F(y)*

We distinguish two types of copulas, elliptic and Archimedean. The first group presents the normal and t-student copulas, their distribution functions are symmetric. The dependence structure is the linear coefficient of correlation that belongs to the interval [-1,1]. The Archimedean copulas are generally used in EVT applications. The specificity of these copulas is that they allow tail dependences.

2) SJC Copula

We retain the SJC copula (static and time-varying) because it's the only asymmetric copula that concentrate simultaneously on upper and lower tail dependence, its expression is as following:

$$C_{SJC}(u,v|\tau^U,\tau^L) = 0.5(C_{JC}(u,v|\tau^U,\tau^L) + C_{JC}(1-u,1-v|\tau^U,\tau^L) + u + v - 1$$

Where;

τ^U, τ^L are the parameters that measure upper and lower tail dependence, respectively. Their time-varying equations are as following;

$$\tau_t^U = \Lambda(\omega_U + \beta_U\tau_{t-1}^U + \alpha_U \times \frac{1}{10}\sum_{j=1}^{10}|u_{t-j} - v_{t-j}|$$

$$\tau_t^L = \Lambda(\omega_L + \beta_L\tau_{t-1}^L + \alpha_L \times \frac{1}{10}\sum_{j=1}^{10}|u_{t-j} - v_{t-j}|$$

Where Λ constitute the logistic transformation that keeps the parameters in the interval [0,1]. τ_t^U et τ_t^L are modeled as an ARMA(1,1) ; the lags of innovations are measured as $\frac{1}{10}\sum_{i=1}^{10}|u_{t-i}v_{t-i}|$. This is a way to incorporate the time-varying in the dependence.

IV. EMPIRICAL ANALYSIS

A. Data description:

Our study focuses on daily data for three stock indices; Nikkei 225 (Japan), CAC40 (France) and Bovespa (Brazil). We chose the SGI FX - G10 Carry Trade Index as a proxy of the CT strategy. Our data were collected from SOCIETE GENERAL INDEX and yahoo finance website for the period 05 January, 2000 to 25 July, 2014.

For all returns[1], we did not reject the hypothesis of stationarity. The descriptive statistics for each return show a mean approximately equal to zero, exhibit negative skewness and excess kurtosis. The Jarque–Bera statistic indicates that the series are not normally distributed, which justifies the application of copula functions.

B. Empirical results:

1) Marginal distribution modeling

Our search for an appropriate AR-GARCH model led us to retain the AR (0) -EGARCH (2, 1) for CT, AR (0) -TARCH (1, 1) for Japan, AR (1) -EGARCH (1,1) for France, and AR (0) -TARCH (2.1) for Brazil. The fitted residuals are *i.i.d* distributed; the values of Ljung-Box Q and Q² confirm the absence of autocorrelation and heteroscedasticity, which mean that GARCH models was well specified.[2]

Moving to POT approach, we set the upper and lower thresholds to be 10% of the residuals for each tail. We use maximum likelihood estimation method in order to obtain GPD parameters and fit the model.

From the table 1, we can see tail parameters that are estimated from GPD. The values of *u* for each index are between 1.14 and 1.22 for the right tail and 1.26 and 1.31 for the left tail. The shape parameter exhibits high values regardless the sigh which reflects heavy tails especially in the left part. Japan has the heaviest lower tail with a value of 0.038 indicating that the probability of occurrence of extreme losses in much larger than the probability of extreme profits.

TABLE 1
THE ESTIMATED TAILS FROM GPD

	Carry Trade	Japan	France	Brazil
		Upper Tail		
u	1.15	1.21	1.16	1.22
ξ	-0.087	-0.239	-0.055	-0.055
ψ	0.565	0.539	0.475	0.507
		Lower Tail		
u	1.27	1.31	1.29	1.26
ξ	-0.061	0.038	-0.047	-0.042
ψ	0.681	0.591	0.682	0.639

However, our aim here is to answer the question whether the link between the CT returns and stock markets is regime-dependent. So, after obtaining the GPD parameters, we fit these marginal distributions into the copula function.

2) Estimating SJC-Copula

We present in table 2 the estimated static and time-varying parameters of SJC copula. For the static copula, the parameters of dependence *CST U.Tail* and *CST L.Tail* measure the degree of dependence between the CT and stock markets in the upper and lower tail, respectively. For the dynamic copula, ω permits to describe of dependence level, β is the autoregressive term that captures any persistence of dependence, and α is a forcing variable that captures variation in the dependence.

TABLE 2
ESTIMATION OF JOINT COPULA PARAMETERS

	CT-Japan	CT-France	CT-Brazil
STATIC SJC			
CST-	0.00027	0,1257	0,051
U. Tail	(0.001)	(0.028)	(0,024)
CST -	0.1113	0,2410	0,1738
L. Tail	(0.026)	(0.025)	(0,025)
LL	50.61	197.786	114.99
AIC	-97.22	-391.57	-225.9
BIC	-85.378	-379.73	-214.1
TIME-VARYING SJC			
ω_U	-2,789	0,2151	0,7
	(0,006)	(0,1232	(0,26)
ω_L	0,248	0,284	0,117
	(0,105)	(0,122)	(0,023)
α_U	-0,208	-1,3477	-4,82
	(0,008)	(0,896)	(1,787)
α_L	-1,214	-1,3364	-0,514
	(0,567)	(0,585)	(0,105)
β_U	3,854	0,9452	0,8
	(8,379)	(0,053)	(0,07)
β_L	0,949	0,9375	0,986
	(0,026)	(0,035)	(0,003)
LL	63,34	279.74	163.96
AIC	-114.68	-547.48	-315.92
BIC	-79.160	-511.96	-280.4

Note; standard errors are reported in parentheses

For all couples, the left tail presents a dependence parameter higher than the right tail, e.g, there is 24.10% of chance that the CT index yields negative returns during CAC40 crash, whereas, there are only 12.57% of chance that the strategy generate profits when stock market performs well. For the couple CT-Japan, the strategy reacts significantly to the Japanese index crash while there is almost no reaction during market boom. Our results indicate that currency CT are significantly exposed to high and increasing volatility in equity markets.

The values of ω_L that are generally higher than ω_U confirm our results. The relation shows a more negative extreme dependence than positive extreme dependence.

To summery, extreme co-movement between CT and stock market returns are more visible during periods of bear while the strategy is slightly affected during booms. The periods of large volatilities stimulate CT unwinding which aggravate the instability and volatility of the markets.

Our reasoning highlights the important impact of investor sentiment. Indeed, losses in CT is stimulated by speculators reaction who are forced to sell their long positions in high interest rate currencies and take back their short positions

[1] The data are transformed in logarithm form and are considered in first difference

[2] The output are available under request

in low interest rate currencies. Studies already show that capital inflows from countries with low interest rate yields to markets with high interest rate yields are related to financial situations. Reference [15] confirms that volatility and skewness could drive investor behavior. In this respect, the sensitivity of this relationship to international disturbances traces the negative effect of financial liberalization, particularly, for high yielding markets.

In addition, the asymmetry observed between upper and lower tail dependence is due to the fact that the shape parameter of losses of each series obtained by EVT approach is higher than that in right tail. Another reason for which the left tail dependence is higher than that of the right tail dependence is explained by several empirical studies that assume that markets tend to crash together than go up together.

To conclude, the CT activities seem cannot defend itself against market crashes, especially in a context of an increasingly globalized world. Therefore, our results cast doubt on the conclusion of [1] whose show that this strategy could be used as asset classes to improve portfolio performance and increase its return.

We believe that CT could produce outstanding returns and increase stock portfolio performance during boom periods but cannot be insurance during troubled times because of its high correlation with stock markets. Even if the including of CT is benefic, the losses of this strategy during crashes are likely to be much higher than the gains generated during booms. So, incorporating CT as a new asset class into investment portfolios will put extra volatility into share price movements which could worsen potfolio performance during stress periods.

V. CONCLUSION

Since 1995, the volume of CT multiplied astronomically which has drawn increasing attention of academia research to study its dependence with stock markets. Theatrical and empirical debates emphasize that their dependence level is stronger during crashes and booms than “normal periods”.

We examine the dependence structure between CT and three stock markets using GARCH-EVT-COPULA. Studying dependence for rare events is extremely important since it allows visualizing how large movements in stock prices (booms and crashes) could affect CT performance. The results indicate that the strategy is strongly related to stock market returns during periods of crashes that period of booms, which traces the significant effect of investor sentiment during extreme events. The existence of high risk aversion exhibits strong lower tail dependence and reduces the weight of interdependence in upper tail.

Thus, the interest of our results lies in two essential points: first, the difference between upper and lower tail dependence highlight the asymmetrical structure of the relationship between CT and stock markets which becomes more intensive during periods of great turbulence. This has not been clearly demonstrated in the literature. By comparing the two tails dependence using SJC copula, we could confirm the significance of negative shocks that have more impact on the level of dependency than positive shocks of same magnitude. Second, our finding contradicts the conclusion of [1] that confirms the capacity of CT to enhance portfolio performance. According to our results, the correlation between the two markets is more important during bear periods; therefore, the CT could not be an appropriate alternative asset because of its crash risk that is more important and exceed CT Sharpe ratios.

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