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Re-examination of risk-return dynamics in international equity markets and the role of policy uncertainty, geopolitical risk and VIX: Evidence using Markov-switching copulas

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ABSTRACT

This study re-examines the empirical relationship between risk and return from 1994m12 to 2020m08 in fifteen international equity markets employing the novel time-varying Markov switching copula models. We provide first-time insightful evidence of time-varying Markov tail dependence structure and dynamics between risk and return in international equity markets. Results show that the dependence structure is positive for USA, UK, Germany, Italy, Brazil, Australia, Taiwan, Canada, Mexico, Japan, France and South Africa and negative for Singapore, India, Japan and China. Finally, we document the effects of policy uncertainty, geopolitical risk and VIX conditional on different markets states.

1. Introduction

According to Leon-Valle et al. (2005) and Chen (2015), the risk-return trade-off relation regarded as a long-standing phenomenon in investment analysis is the foundation of modern financial economics. On the other hand, Ghysels et al. (2005) assert that the risk-return relation which postulates that expected excess return is related positively to the conditional variance is the first fundamental law of finance. Interestingly, even though the risk-return relation has emerged as one of the most debated themes in financial economics, evidence from the empirical literature that focuses on index returns is inconclusive. Campbell (1987), Whitelaw (1994), Brandt and Wang (2010), Chen (2015) document a negative relationship, while studies by Ghysels et al. (2005), Guo and Whitelaw (2006) and Lundblad (2007), find a positive trade-off between risk and return. Several studies have also estimated the empirical trade-off between risk and return using specific markets. Studies such as Glosten et al. (1993), French et al. (1987), Baillie and De Gennaro (1990), Nelson (1991), Bekaert and Wu (2000), Lanne and Saikkonen (2003) all focused on the US markets with mixed results. Other studies such as Theodossiou and Lee (1995), Paudyal and Saldanha (1997), Xing and Howe (2003), Li et al. (2005), Bali

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and Peng (2006) and Salvador et al. (2014) also focused markets including UK, Australia, France, Italy, Japan, Germany, Canada and Belgium with mixed findings. Likewise, emerging stock markets in Europe, Asia and Latin America have also received some attention from the research community (Chui and Wei, 1998; Chiang and Doong, 2001; Tabak and Guerra, 2002; Kovacic, 2008). Concerning stock markets of emerging economies, we find scant studies focusing on the risk-return relationship with most studies focusing on the Johannesburg stock exchange (Suliman, 2012; Mandimika and Chinzara, 2012; Darrat et al., 2012; Tah, 2013).

Majority of earlier studies in this area employed both multivariate and linear GARCH models to examine the risk return relationship (Brandt and Kang, 2004; Ghysels et al., 2005; Pastor et al., 2008; Guo and Whitelaw, 2006; Rapach et al., 2013). However, due to the shortcomings of linear and correlational methodologies and modified versions of GARCH approaches which are often used to model the risk-return trade-off, this study adopts the Markov-switching time-varying copula model (Boubaker and Sghaier, 2016; Tiwari et al., 2021; Abakah et al., 2021) to re-examine the risk-return relationship trade-off in international equity markets.

To the best of our knowledge, this is the first paper to re-examine the risk-return relationship trade-off using variant forms of copulas. The strength of the selected switching Markov time-varying copulas is due to their ability to establish the dependency structures for wavelet decomposed series, accounting for potential different market states. For this estimation technique, the ad hoc determination of change point in the dependence measures is not required. The Markov-switching copulas allow the copula parameter to change, contingent on the condition of the unobserved Markov switching chain analogous transition probabilities (Hamilton and Susmel, 1994). This method aids in assessing the time-varying interdependence structures between expected return and conditional volatility. The examination of the risk-return relationship contributes to the literature in a range of settings, concerning issues such as portfolio diversification across international markets, volatility and investment management, since the findings will aid in global hedging and portfolio formulation strategies.

Our findings contribute to the literature in several ways; (i) our paper is a pioneering effort to explore the tail dependence dynamics between risk and return across international equity markets; (ii) it employs the novel Markov switching copula approach that permits a regime change in the copula parameter estimation in order to measure the time-varying dependency structure. The key benefit of this estimation technique is that the dependence structure does not involve an ad hoc determination of change points (da Silva Filho et al., 2012; Boubaker and Sghaier, 2016). We document several significant findings. First, we find a significant negative tail dependency between risk and return for the following equity markets: Singapore, India, Japan and China, and positive dependence dynamics for the USA, the UK, Germany, Italy, Brazil, Australia, Taiwan Canada, Mexico, Japan, France and South Africa. Second, we observe that the relationship is time varying Markov dependence for all markets examined. Third, from the dependence parameter plots we note that the dynamic dependence is intense irrespective of prevailing market conditions when we compared the variation during crisis periods and normal market conditions. Lastly, we provide evidence that policy uncertainty, geopolitical risk and equity market volatility (VIX) have negative effects on the risk-return relationship for all markets at lower, medium and higher quantile levels.

The remaining parts of the paper are outlined as follows. We present in Section 2 the methodology. Section 3 contains the data and summary statistics while Section 4 reports discussion of results. Section 4 documents the conclusion.

2. Empirical methodology

In this paper, we used various copula models including time invariant, time-variant and Markov switching techniques. Details are discussed in the supplementary file.

3. Data specification and summary statistics

We obtained daily price indices of fifteen international equity markets including Canada, the UK, the USA, Italy, France, Germany, Brazil, Mexico, Japan, China, Australia, Singapore, India, Taiwan and South Africa from Datastream from 30th December 1994 to 24th August 2020. Daily returns are in log form while volatility is measured as absolute returns (Antonakakis and Kizys (2015). The summary statistics of the underlying series are provided in Table 2S and Table 3S in the supplementary file.

4. Empirical discussion

4.1. Results from the marginal distribution

First, we use ARMA filtering process to explore the feature of price returns for each market and absolute returns to confirm that the residuals obtained are free from any autocorrelation effect. Next, we use an ARCH-LM test to examine the ARCH effects of the fitted series with results showing proof of heteroscedasticity across all series. We establish the optimal lag length in each of the univariate GARCH and fit specifications to the second moments. From Table 4S and Table 5S, we present the estimated output of the ARMA-GARCH models for the return series and absolute returns of the fifteen equity markets under examination. Based on the Akaike Information Criterion (AIC) value, we select the best fit model. Using the Akaike Information Criterion (AIC), we note that the best fit model is ARMA (1, 0) - GARCH (1, 1) for all the returns and absolute returns of the fifteen international equity markets. After confirming the bit fit model through the marginal specifications, we move to the next step where we applied the empirical distribution

¹ Available in the supplementary file.

function (ecdf's) to convert the standardized i.i.d. residuals into identical margins. Next, we use the ARCH-LM test and the Ljung-Box test to conduct goodness of fit tests on the probability integral transform (PIT) residuals of the fundamental error terms for each of the ARMA-GARCH (p,q) procedures. From Panel-C of Table 4S and Table 5S, we document the absence of autocorrelation across all series which validates the suitability of the marginal models.

4.2. Results from copula estimation

We discuss the tail dependency structures between risk and return and depend on the log likelihood estimate to select the best copula fit estimated model.

First, the risk-return trade off tail dependence structures for all markets are estimated using the time-invariant copulas in Panel A of Table 1. We note that student—t copula is the best copula fit for modelling the risk-return trade-off for Canada, the UK, the USA, Italy, France, Germany, Brazil, Mexico, Japan, China, Singapore, India, Taiwan and South Africa. Student-t copula shows series' symmetric upper tail and lower tail dependence structures which confirms the co-movement during both good and good market states. The symmetric dependence in risk-return trade-off for these countries suggests that the variables are intertwined based on the Tau estimate which reveals marginal dependence between risk and return. For the case of Australia, we note that the Symmetrized Joe copula (SJC), which captures the dependence behaviour of the lower and upper tails, best captures the relationship. Overall, we find a positive tail dependence between risk and return for the markets under examination using time invariant copulas.

However, following the drawbacks of static copulas and the extent of volatility changes in equity markets, we perform additional analysis time-variant and time-variant Markov switching copulas to further test the sign and magnitude of the risk-return relationship trade off across the fifteen equity markets under examination.

In Panel-B and Panel-C of Table 1, we present results for the dependence between risk and return using time variant and time-varying Markov switching copulas. We note that for the case of Canada, Mexico, Japan and France, time varying Rotated Clayton copula is the best copula fit that accurately captures the risk-return trade-off for these equity markets, using the LL estimate with a significant negative dependence structure. Consequently, a look at the probabilities ρ and q for the dependence between risk and return for these four equity markets (Canada, Mexico, Japan and France) confirms that the dependence structure is Markov-switching time-varying. Focusing on the estimates of β^2 for each markets, we find they are significant, which further suggests that the relationships between risk and return for these markets are time-varying. Relying on the sign of β , we can confirm the nature of the dependency structure between risk and return for these markets.

From Panel-C of Table 1, we find a positive dependence structure for the Canadian, Mexican and French equity markets, which means the risk and return relationship for these markets modelled accurately using time-varying Markov rotated clayton copula comove in the same direction. However, we note a negative dependence structure for the return- risk relationship for Japan. This connotes that for Japanese equity markets, risk and return move in an opposite direction, thus investors could gain for holding a portfolio with such assets. Concerning the nature and magnitude of the dependence structure between risk and return the remaining markets under examination, we observe that for the case of the USA, the UK, Germany, Italy, Brazil, Australia, Singapore, India, China and South Africa, results from Table 1 Panel-C show that the time-variant Normal Markov switching copula is the best copula fit model for these markets. Subsequently, a look at the probabilities ρ and q for the dependence between risk and return for these markets shows that the dependence structure for each of these markets is Markov-switching time-varying.

Next, to examine the nature of the dependence structure, we focus on the estimates of \$\beta for each market. From the sign of \$\beta\$, the nature of the dependence structure is established. From Table 1 Panel-C, we find a negative relationship between risk and return for Singapore, India and China, while the dependence is positive for the USA, the UK, Germany, Italy, Brazil, Australia, and South Africa. The negative dependence structure between risk and return suggests that the variables move in opposite directions while the positive dependence suggests the risk and return move in the same direction. With regarding to Taiwanese equity markets, time varying Clayton Markov copula emerged to be the best fit model able to capture the risk return relationship with the risk return dependence structure being positive. Comparing our results with earlier studies, our findings of a positive dependence structure for the USA market is in consonance with the findings of Ghysels et al. (2005), Lanne and Saikkonen (2003), Guo and Whitelaw (2006) and Lundblad (2007) who documented a positive trade-off between risk and return for the USA market. For the South African markets, our findings differ from the few existing studies that documented a negative significant relationship between risk and return (e.g., Darrat et al., 2012). For the case of our findings regarding Europe's equity markets, these being the UK, Italy, France, Germany, we document findings similar to the conclusion of Salvador et al. (2014) who documented a positive relationship after relaxing the linear assumption. The findings on China which show a positive dependence time varying structure is not in agreement with the findings of Chen (2015) but in agreement with Chen (2013). In the case of Taiwan, Chiang and Doong (2001) documented findings similar to ours. Overall, our findings indicating that the risk-return relationship is time-varying Markov switching and not static or linear supports the school of thought that maintaining the linear assumption in the risk-return trade-off leads to insignificant estimation (Yang, 2011; Salvador et al., 2014; etc.).

In our quest to further validate our earlier findings, we conduct additional analysis using the time-varying dependence parameter plots for each market's risk and return trade-off in Figure 2S. We observe that the dependence structure between risk and returns for all the markets examined varies with time both in bearish and moderate market conditions. In brief, the dependence structure varies

² In Table 1, the estimates for standard errors are not reported for simplicity purposes and would be made available upon request.

³ Available in supplementary file

Table 1.

Estimation of the dependence-switching copula model for returns and volatility per country.

	Canada	USA	UK	Germany	France	Italy	Brazil	Mexico
Panel A: Parameter Estimates for time-in	variant copulas							
formal Copula	· · · · · · · · · · · · · · · · · · ·							
•	0.0182	0.0158	0.0006	0.0052	0.0081	-0.0105	-0.0043	0.0061
og-like	-1.1095	-0.0008	0.0000	-0.0001	-0.2202	-0.3698	-0.0001	-0.0001
layton's copula								
	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
og-like	0.1211	0.0001	0.0001	0.0001	0.1339	0.1407	0.0001	0.0001
Rotated Clayton copula	0.0707	0.0756	0.2644	0.2670	0.2725	0.2410	0.2520	0.2005
x Log-like	0.3727 -292.17	0.3756 -0.2922	0.3644 -0.2910	0.3679 -0.2962	0.3735 -303.47	0.3412 -266.07	0.3529 -0.2774	0.3805 -0.3149
Log-like Plackett copula	-292.1/	-0.2922	-0.2910	-0.2902	-303.47	-200.07	-0.2//4	-0.3149
S	1.2523	1.2741	1.1183	1.1318	1.1386	1.0614	1.1005	1.1002
.og-like	-14.5018	-0.0168	-0.0036	-0.0044	-4.8422	-1.0215	-0.0026	-0.0026
Frank Copula		2.2200		2.3011				2.0020
	0.3826	0.4113	0.1899	0.2102	0.2210	0.1015	0.1622	0.1615
.og-like	-12.3031	-0.0142	-0.0030	-0.0037	-4.1206	-0.8700	-0.0022	-0.0022
Gumble Copula								
5	1.1493	1.1509	1.1403	1.1419	1.1432	1.1308	1.1361	1.1450
Log-like	-240.116	-0.2396	-0.2373	-0.2450	-249.63	-216.72	-0.2272	-0.2566
Rotated Gumble Copula	1 1000	1 1000	1 1000	1.1000	1 1000	1 1000	1.1000	1 1000
5	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000
og-like	137.9048	0.1383	0.1590	0.1547	154.19	168.067	0.161	0.1580
tudent's t copula	0.0610	0.0661	0.0283	0.0326	0.0358	0.0119	0.0220	0.0239
	2.2005	2.1607	2.1297	2.1179	2.1621	2.1547	2.1104	2.1000
og-like JC Copula	-487.078	-0.5068	-0.5114	-0.5124	-498.67	-498.133	-0.5171	-0.5252
JC Copula _U	0.2650	0.2682	0.2600	0.2615	0.0047	0.2441	0.2517	0.2692
U L	0.2030	0.2082	0.0000	0.2013	0.0047	0.0000	0.2317	0.0000
.og-like	-342.089	-0.3454	-0.3425	-0.3510	-103.35	-310.279	-0.322	-0.3754
Panel B: Parameter Estimates of time-var				,,,,,,,				2.3701
TVP Normal copula								
, ,	0.09804	0.0139	0.0048	0.0220	0.0249	-0.0017	0.0205	0.0723
y_1	0.30830	-0.0083	0.0276	0.0772	0.0353	0.0380	0.2426	0.2335
I_2	-1.85164	1.0743	-0.5310	-0.5129	-0.5934	1.6298	-1.1329	-2.0002
.og-like	-9.2061	-0.0009	-0.0001	-0.0009	-0.3728	-5.3928	-0.0067	-0.0150
VP Clayton copula								
J_{o}	0.00031	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003
ν ₁	-3.09219	-3.1457	-2.8825	-2.8953	-2.7519	-2.7823	-3.0676	-3.1207
12 og like	0.00000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
og-like VP Rotated Clayton copula	0.121	0.0001	0.0001	0.0001	0.1338	0.1406	0.0001	0.0001
· · · · · · · · · · · · · · · · · · ·	1.33605	0.7980	1.0371	0.9702	0.3533	0.4414	1.3597	1.3926
f_0	-0.60949	-0.2123	-0.8038	-0.3392	0.7351	0.6071	-0.7518	-0.5624
y_2	-1.48040	-0.3172	-0.3997	-0.7076	-0.0556	-0.1963	-1.4268	-1.6150
og-like	-307.468	-0.2931	-0.2924	-0.3005	-307.27	-272.077	-0.2948	-0.3356
VP Gamble copula								
2	1.84151	-0.3866	-0.4680	1.4012	0.9540	-0.7776	2.0308	1.8044
1	-1.02366	0.6638	0.7101	-0.8009	-0.4817	1.0346	-1.2498	-0.9821
	-0.82614	0.0329	0.0970	-0.3246	-0.0741	-0.0935	-0.6857	-0.8532
og-like	-248.35	-0.2396	-0.2382	-0.2463	-249.71	-219.571	-0.2344	-0.2673
VP Rotated Gumble copula	0.00504	0.0100	0.0100	0.0050	0.0010	0.0000	0.0000	0.0000
) U	0.02526	0.0193	0.0199	0.0250	0.0218	0.0000	0.0000	0.0000
<i>u</i> U	-0.02525 -0.00002	-0.0193 0.0000	-0.0199 0.0000	-0.0250 0.0000	-0.0218 0.0000	0.0000 0.0000	0.0000	0.0000
u.og-like	-0.00002 0.0915	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
VP SJC copula	0.0713	0.0001	0.0002	0.0001	0.144/	0.0041	0.0004	0.0011
vr 350 copula	1.87455	-0.2433	0.7648	0.5397	-0.0167	-1.7713	1.9674	2.1984
ับ	-5.89733	-1.3019	-1.5749	-2.9547	-1.5372	-0.9270	-5.5611	-6.8785
U	-3.86038	-1.4079	-5.1080	-2.4611	-2.0387	3.7957	-4.8136	-3.4437
OL .	-21.05855	-22.983	-21.086	-22.420	-20.989	-22.5732	-20.792	-21.170
L	-0.03487	0.0000	0.0059	0.0042	-1.2575	-0.0446	-0.0039	-0.0172
L .	-280.43	0.0000	0.0000	0.0000	-0.0039	-0.0001	0.0000	0.0000
og-like	1.87455	-0.2675	-0.2636	-0.2736	-278.25	-237.717	-0.2615	-0.3110
anel C: Parameter Estimates for time-va	rying Markov copi	ıla						
Time-varying Normal Markov copula					. = =			
$\mathcal{O}_{c,}^{0}N$	-0.6536	-0.6606	-0.7637	-0.9602	-4.2378	-0.8583	-0.9103	-0.5245
	0.010000	0.0000	0.0055	0.1604	0.0045	0.1500	0.1504	0.0191
	0.018022	0.0030	0.0955	0.1694	2.0945	0.1723	0.1594	0.0191

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Table 1. (continued)

	Canada	USA	UK	Germany	France	Italy	Brazil	Mexico
$\omega_{c,}^{1}N$								
$\beta_{c,N}$	2.132445	2.1778	1.9616	1.7886	-2.4442	1.7605	1.8021	2.1178
α_{c} , N	-0.07908	-0.0692	-0.1396	-0.1056	-0.4056	-0.0738	-0.0804	-0.0363
ρ	-4.69045	-0.2665	-0.1654	-0.3335	-0.2137	-0.1184	-3.6826	-3.8028
q	5.690449	1.2665	1.1654	1.3335	1.2137	1.1184	4.6826	4.8028
Log-like	-480.97	-0.4661	-0.4481	-0.4409	-415.52	-416.785	-0.4873	-0.4689
Time-varying Clayton Markov copulas $\omega_c^0 C$	0.09679	0.0075	-0.0001	-0.0155	0.0598	0.0449	0.0300	0.0160
-,	-1.90475	-1.8881	-0.0001	-1.7498	-1.8323	-1.8733	-1.8919	-1.9169
$\omega_{c,C}^{1}$								
$\beta_{c,C}$	-0.12254	-0.1318 -0.0268	1.4340	-0.1443	-0.1314 -0.1815	-0.1300 -0.1267	-0.1295	-0.1307
$\alpha_{c,C}$	-0.31638		0.0000	0.0599 0.3948	0.0130	-0.1267 -0.1193	-0.0996	0.0157 -0.1452
$rac{ ho}{q}$	0.343953 0.656047	0.3136 0.6864	0.5000 0.5000	0.5948	0.0130	-0.1193 1.1193	-0.0308 1.0308	-0.1452 1.1452
Log-like	10.3288	0.0053	0.0001	0.0044	-0.4505	-3.3739	-0.001	-0.0020
Time-varying Rotated Clayton Markov								
copulas $\omega_c^0 RC$	-0.10096	0.3028	0.4318	0.0745	0.1024	0.2403	0.0323	-0.1119
ω_c , RC	-1.57517	-0.4825	-0.3796	-1.5011	-1.4388	-1.2960	-1.5118	-1.6743
$\omega_{c,RC}$ $\beta_{c,RC}$	0.378163	-0.2883	-0.2806	0.4761	0.4419	0.4980	0.4768	0.4432
$ \rho_{c,RC} $ $ \alpha_{c,RC} $	0.378103	-0.2883 -0.7844	-0.2800 -1.0663	-0.1984	-0.2848	-0.6295	-0.0829	0.4432
	0.695285	0.4661	0.3881	0.4582	0.4638	0.5060	0.6302	0.5480
$rac{ ho}{q}$	0.304715	0.5339	0.6119	0.5418	0.5362	0.4940	0.3698	0.4520
Log-like	-451.555	-0.4571	-0.4437	-0.4328	-438.45	-383.819	-0.4228	-0.4757
Time-varying Gumbel Markov copulas								
$\omega_{c,}^0 G$	-0.00466	-0.7002	-0.4318	-0.0934	-0.1515	-0.6676	-0.2388	-0.0363
$\omega^1_{c,}G$	-0.5244	-1.4746	-1.1331	-0.6015	-0.8018	-1.4094	-1.0405	-0.5495
$\beta_{c,G}$	0.432602	0.2477	0.3161	0.4151	0.3405	0.2393	0.2449	0.4110
$\alpha_{c,G}$	0.303355	2.8013	1.7924	0.5382	1.0603	2.4857	1.6605	0.4585
ρ	0.729618	0.2606	0.2498	3.1329	0.1241	0.2046	-4.5922	0.8756
q Log-like	0.270382 -305.964	0.7394 -0.3116	0.7502 -0.3034	-2.1329 -0.2941	0.8759 -297.56	0.7954 -257.273	5.5922 -0.2863	0.1244 -0.3277
Time-varying Rotated Gumbel Markov copulas	-303.304	-0.3110	-0.3034	-0.2541	-277.50	-23/.2/3	-0.2003	-0.3277
$\omega_c^0 RG$	-1.16E-05	-2.0047	-3.1664	3.0684	0.0000	0.0000	0.0000	0.0000
$\omega_c^1 RG$	-1.16E-05	-2.0047	-3.1664	3.0686	0.0000	0.0000	0.0000	0.0000
$\beta_{c,RG}$	1.16E-05	2.0043	3.1586	-3.0782	0.0000	0.0000	0.0000	0.0000
α_{c} , RG	1.22E-08	0.0006	0.0246	0.0267	0.0000	0.0000	0.0000	0.0000
ρ	0.5	0.5000	0.5005	0.5157	0.5000	0.5000	0.5000	0.5000
q	0.5	0.5000	0.4995	0.4843	0.5000	0.5000	0.5000	0.5000
Log-like	0.0915	0.0001	0.0001	-0.0001	0.1227	0.0041	0.0004	0.0011
Time-varying SJC Markov copulas	1.674614	-2.1304	0.7916	1.6153	1.6344	-1.2669	6.2618	-7.6189
$\omega_{c}^{0}U$	-5.64178	-2.1304			0.8351	-11.1270	0.2688	-3.4438
$\omega_{c,}^{1}U$			-0.0578	0.6747				
$\beta_{c,U}$	-17.85	-10.720	0.7648	-0.9087	-0.9295	-1.7709	1.5561	2.1984
α_{c} , U	-15.3041	-22.577	-20.604 5 1070	-12.908	-12.940	-21.2017	-12.993 5.0001	-13.3219
$rac{ ho}{q}$	-1.9207 16.58504	3.9404 -1.3234	-5.1079 -8.4643	0.4469 -2.8021	0.4745 -2.7045	3.7948 -8.1574	-5.0091 -2.7159	-3.4431 22.0586
Log-like	-1.5921	-0.3577	-1.5747	-0.2689	-2.7043	-237.829	-0.2649	-0.3110
Ü	Japan	Australia	Singapore	India	China	Taiwan	South Afri	ca
Panel A: Parameter Estimates for time-inva Normal Copula	riant copulas							
P	-0.0109	0.0047	-0.0060	0.0063	-0.0077	0.0024	-0.0015	
Log-like	-0.0004	-0.0001	-0.1200	-0.0001	-0.0002	0.0000	0.0000	
Clayton's copula α	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	
Log-like	0.0001	0.0001	0.1397	0.0001	0.0001	0.0001	0.0001	
Rotated Clayton copula								
α	0.3592	0.3732	0.3457	0.3732	0.3655	0.3855	0.3606	
Log-like	-0.2947	-0.2965	-275.916	-0.3047	-0.3057	-0.3227	-0.287	
Plackett copula δ	1.0073	1.1676	1.0388	1.1186	0.9996	1.0761	1.1061	
Log-like	0.0000	-0.0069	-0.4199	-0.0036	0.0000	-0.0015	-0.0029	
Frank Copula								

(continued on next page)

Table 1. (continued)

	Canada	USA	UK	Germany	France	Italy	Brazil	Mexico
	0.0124	0.2632	0.0651	0.1900	0.0002	0.1242	0.1713	
og-like	0.0000	-0.0058	-0.3594	-0.0030	0.0000	-0.0013	-0.0025	
umble Copula								
an libe	1.1337	1.1456	1.1313	1.1426	1.1356	1.1447	1.1388	
og-like otated Gumble Copula	-0.2362	-0.2393	-228.247	-0.2523	-0.2531	-0.2615	-0.2322	
otated dumble copula	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	
og-like	0.1764	0.1534	167.5649	0.1555	0.1723	0.1645	0.1608	
tudent's t copula								
	-0.0002	0.0415	0.0059	0.0262	-0.0041	0.0200	0.0241	
	2.1302	2.1222	2.1771	2.1002	2.1000	2.1000	2.1299	
og-like	-0.5071	0.1534	-486.804	-0.5259	-0.5589	-0.5306	-0.5093	
JC Copula	0.0550	0.0660	0.0455	0.0040	0.0001	0.0704	0.0500	
U	0.2559 0.0000	0.2663 0.0000	0.2457 0.0000	0.0042 0.0000	0.2601 0.0000	0.2734 0.0000	0.2580 0.0000	
z og-like	-0.3378	-0.5163	-322.539	-0.1020	-0.3660	-0.3815	-0.3394	
anel B: Parameter Estimates of time-varyi		-0.5105	-322.337	-0.1020	-0.3000	-0.3013	-0.5574	
VP Normal copula	ng copulas							
0	-0.0482	0.0425	0.0410	0.0739	-0.0022	0.0415	0.0329	
1	-0.1827	0.2755	0.5280	0.4602	0.6305	0.3471	0.3229	
2	-0.8278	-0.4927	-1.4962	-1.2024	-1.7836	-1.8318	-1.7903	
og-like	-0.0038	-0.012	-30.1386	-0.0227	-0.0427	-0.0098	-0.0092	
VP Clayton copula	0.0000	0.0000	0.0002	0.0000	0.0000	0.0004	0.0000	
o '-	0.0003 -2.9711	0.0003 -3.4416	0.0003 -3.0009	0.0003 -3.3750	0.0003 -3.1227	0.0004 -3.5370	0.0003 -3.3984	
1 2 2	0.0000	-3.4416 0.0000	-3.0009 0.0000	-3.3750 0.0000	0.0000	0.0000	-3.3984 0.0000	
og-like	0.0002	0.0001	0.1396	0.0001	0.0001	0.0001	0.0001	
VP Rotated Clayton copula								
To	0.3431	1.1981	1.5094	1.3473	1.4465	1.3738	1.2657	
1	0.7465	-0.3356	-0.4178	-0.3644	-0.7057	-0.7153	-0.7157	
2	-0.0363	-1.3750	-2.2680	-1.7663	-1.7135	-1.3954	-1.2032	
og-like	-0.2958	-0.3118	-319.734	-0.3324	-0.3335	-0.3361	-0.2961	
VP Gamble copula	1.4252	1.2744	1.5917	1.4316	2.0476	1.9748	1.9264	
	-1.0355	-0.5782	-0.6834	-0.6436	-1.1457	-1.1730	-1.1666	
	0.3399	-0.6839	-1.3257	-0.9279	-1.0965	-0.7322	-0.6612	
og-like	-0.2374	-0.2459	-254.416	-0.2658	-0.2738	-0.2682	-0.2373	
VP Rotated Gumble copula								
U	0.0000	0.0000	2.4371	0.0313	0.0354	0.0290	0.0254	
U	0.0000	0.0000	-2.4354	-0.0313	-0.0354	-0.0290	-0.0254	
U	0.0000	0.0000	-0.0036	0.0000	0.0000	0.0000	0.0000	
og-like VP SJC copula	0.0001	0.0002	0.0543	0.0001	0.0001	0.0002	0.0001	
ve SJC copula	-0.5360	1.5867	2.3576	1.8722	2.2733	1.6085	1.7911	
U U	1.4766	-5.8207	-8.5795	-7.0582	-6.8607	-5.0530	-5.2491	
U	-4.2342	-2.7755	-2.7695	-2.3139	-4.1911	-3.4073	-4.5593	
L	-22.1875	-20.5654	-21.6527	-20.9279	-22.0245	-21.163	-21.1645	
L	-1.4462	-0.0002	-0.0024	-1.3781	-0.0126	-0.0077	-0.0081	
L	-0.0053	0.0000	0.0000	-0.0047	0.0000	0.0000	0.0000	
og-like	-0.263	-0.2823	-281.612	-0.3039	-0.3024	-0.0002	-0.2657	
anel C: Parameter Estimates for time-vary ime-varying Normal Markov copula	ing Markov cop	oula						
C N	-1.9495	-0.5280	-4.1634	-3.9100	-3.5830	0.0000	-0.5131	
=)								
$^{1}_{c,}N$	2.8444	-0.0084	1.9132	1.9140	2.2039	0.0000	0.0084	
$_{c}$, N	-1.8763	2.1829	-2.3757	-2.0135	-2.4062	0.0000	2.1421	
$_{c,N}$	-0.1852	-0.0394	0.3170	0.6029	0.5431	0.0000	-0.0531	
	0.6711	-0.5206	-7.1291	-0.3952	-0.6288	0.0000	-0.4173	
	0.3289	1.5206	8.1291	1.3952	1.6288	0.0000	1.4173	
og-like	-0.3803	-0.4519	-458.129	-0.4811	-0.5093	-0.3098	-0.4415	
ime-varying Clayton Markov copulas	0.0001	0.0250	0.0252	0.0101	0.0001	0.4006	0.1004	
⁰ , C	-0.0001	0.0358	-0.0353	0.0181	-0.0001	-0.4926	0.1004	
$^{1}_{c,}C$	-0.0001	-1.3502	-1.9686	-1.7750	-0.0001	0.0233	-1.8053	
_{c,} C	1.3732	-0.1801	-0.1265	-0.1395	1.4329	2.1010	-0.1295	
c, C	0.0000	-0.0971	-0.0197	-0.0462	0.0000	-0.0236	-0.3052	
c, -								
	0.5000	-0.0370	-0.2133	0.0740	0.5000	-1.1208	0.3479	
-, -	0.5000 0.5000	-0.0370 1.0370	-0.2133 1.2133	0.0740 0.9260	0.5000 0.5000	-1.1208 2.1208	0.3479 0.6521	

(continued on next page)

Table 1. (continued)

	Canada	USA	UK	Germany	France	Italy	Brazil	Mexico
Time-varying Rotated Clayton Markov copulas								
$\omega_{c,}^{0}RC$	-1.0551	2.2964	-0.1690	-0.0368	-0.1872	0.0210	-0.0637	
$\omega_c^1 RC$	-2.2651	1.0469	-1.5685	-1.4618	-1.7482	-1.8729	-1.5718	
$\beta_{c.}RC$	-0.0096	-0.1318	0.2989	0.3275	0.4009	-0.1317	0.4452	
$\alpha_{c,}RC$	5.0079	-4.6967	0.4191	0.0961	0.5306	-0.0665	0.1796	
ρ	0.5321	1.7743	0.3893	0.5279	0.4171	-0.0655	0.6054	
q	0.4679	-0.7743	0.6107	0.4721	0.5829	1.0655	0.3946	
Log-like	-0.4076	-0.4331	-438.552	-0.4634	-0.4895	0.0013	-0.4276	
Time-varying Gumbel Markov copulas	0.0006	0.0644	1 7101	0.0701	0.0001	0.0000	0.1000	
$\omega_{c,G}^{0}$	-0.3326	-0.0644	1.7191	-0.0781	0.0921	-0.0370	-0.1392	
$\omega_{c,G}^1$	-0.0229	-0.7094	0.6665	-0.5615	-0.4300	-1.4253	-0.6186	
$eta_{c,G}$	0.3627	0.3807	-0.4459	0.4308	0.4801	0.3045	0.4937	
$\alpha_{c,G}$	0.6641	0.6568	-0.4333	0.4701	-0.2693	0.0988	0.3304	
ρ	0.3324	1.1475	0.7899	0.6052	0.7427	0.6263	0.7770	
<i>q</i>	0.6676	-0.1475	0.2101	0.3948	0.2573	0.3737	0.2230	
Log-like Time-varying Rotated Gumbel Markov copulas	-0.2461	-0.2893	-300.361	-0.3151	-0.3384	-0.4742	-0.2833	
$\omega_{c,RG}^{0}$	0.0000	0.0000	2.4373	0.1082	-0.0001	-0.0700	-0.0001	
$\omega_{c}^{1}RG$	0.0000	0.0000	2.4373	-0.4656	-0.0001	-0.6133	-0.0001	
$\beta_{c,RG}$	0.0000	0.0000	-2.4356	0.4210	0.0001	0.4260	0.0001	
$\alpha_{c,RG}$	0.0000	0.0000	-0.0036	0.1441	0.0000	0.4367	0.0000	
ρ	0.5000	0.5000	0.5000	0.7381	0.5000	0.7587	0.5000	
q	0.5000	0.5000	0.5000	0.2619	0.5000	0.2413	0.5000	
Log-like	0.0001	0.0002	0.0543	-0.0011	0.0001	-0.3136	0.0001	
Time-varying SJC Markov copulas	-2.6792	1.2584	3.3177	4.6589	3.5678	-16.413	1.5196	
$\omega_{c,}^{c}U$	-2.0792 2.9187							
$\omega_{c_i}^1 U$		-21.4398	-21.6711	-7.1862	-20.4121	-20.286	0.8519	
$eta_{c,}U$	-0.5376	-10.4803	-8.9230	1.8724	-13.1781	2.0278	-0.9387	
$lpha_{c},U$	-21.4643	-22.7914	-10.8914	-13.1554	-23.5039	-11.219	-12.9102	
ρ	-4.2394	-2.1978	-2.8043	-2.3133	-3.5936	-2.8889	0.4770	
q Log-like	-7.8223 -0.263	10.1988 -0.3492	11.4050 -348.791	-0.7907 -0.3040	-10.0504 -0.3935	-3.3221 -0.381	-2.7521 -0.2627	

Time-varying T Markov copulas. Convergence was not achieved in any of the models; hence results are not presented.

Notes: This table reports the ML estimates for the different static and dynamic bivariate copula models per country. The minimum loglikelihood value

for both low and high dependency regimes with the dependency seen to be either negative or positive in both regimes

4.3. The effects of policy uncertainty, geopolitical risk and VIX on the dependence structure between risk and return

A strand of the literature also argues that macroeconomic factors affect measurement of the risk-return relation and as such should be accounted for in estimating the risk return nexus (De Long et al., 1990; Baker and Wurgler, 2006). Hence, we examine the effects of economic policy uncertainty, geopolitical risk and equity market volatility on the relationship between risk and return. Using quantile regression (QR), we find that policy uncertainty, geopolitical risk and VIX have a negative influence on the risk-return dynamics, which is not surprising since prior studies document the effects of these variables on varied asset classes. The results suggest these factors can divert diversification benefits during extreme and normal markets conditions as shown in Table 6S in the supplementary file.

5. Conclusion

(value on bold) indicates the best copula fit.

This paper provides first time empirical evidence on the dependence structure between the risk-return trade-off in fifteen international equity markets using Markov switching copulas. First, we find a negative tail dependence between risk and return for Singapore, India, Japan and China, and a negative dependence dynamic for USA, the UK, Germany, Italy, Brazil, Australia, Taiwan Canada, Mexico, Japan, France and South Africa equity markets. Lastly, we provide evidence that policy uncertainty, geopolitical risk and equity market volatility (VIX) have negative effects on the risk-return relationship conditional on different markets.

Our findings have several implications. Our findings stress the perils of the linearity assumption when analysing the relationship between risk and return. This connotes that earlier studies the employed linear models fail to capture the global behaviour between risk and return in international equity markets. Hence, it is essential that any analysis of the relationship between risk and return takes into account the time varying properties of the series. From the policy perspective, policy makers' understanding and knowledge of

whether a strong dependence structure exists between risk and return can help them program specific policies that can help mitigate the long and short term impacts of fluctuations on the risk-return trade-off.

Declaration of Competing Interest

There is no conflict of interest with the publication of the present manuscript.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2021.102535.

References

Abakah, E.J.A., Addo Jr., E., Gil-Alana, L.A., Tiwari, A.K., 2021. Re-examination of International bond market dependence: Evidence from a pair copula. Int. Rev. Financ. Anal., 101678

Antonakakis, N., Kizys, R., 2015. Dynamic spillovers between commodity and currency markets. Int. Rev. Financ. Anal. 41, 303-319.

Bali, T.G., Peng, L., 2006. Is there a risk-return trade-off? Evidence from high-frequency data. J. Appl. Econometr. 21 (8), 1169-1198.

Baillie, R.T., DeGennaro, R.P., 1990. Stock returns and volatility. J. Financ. Quant. Anal. 25, 203-214.

Bekaert, G., Wu, G., 2000. Asymmetric Volatility and Risk in Equity Markets. Rev. Financ. Stud. 13, 1-42.

Boubaker, H., Sghaier, N., 2016. Markov-switching time-varying copula modeling of dependence structure between oil and GCC stock markets. Open J. Stat. 6 (4), 565–589.

Brandt, M., Wang, L., 2010. Measuring the Time-Varying Risk-Return Relation from the Cross-Section of Equity Returns, Duke University, Manuscript,

Brandt, M.W., Kang, Q., 2004. On the relationship between the conditional mean and volatility of stock returns: a latent VAR approach. J. Financ. Econ. 72, 217–257. Campbell, J.Y., 1987. Stock returns and the term structure. J. Financ. Econ. 18, 373–399.

Chen, M., 2015. Risk-return trade- off in Chinese stock markets: some recent evidence. Int. J. Emerg. Mark. 10 (3), 448-473.

Chiang, T.C., Doong, S.-.C., 2001. Empirical analysis of stock returns and volatility: evidence from seven Asian stock markets based on TAR-GARCH model. Rev. Ouant. Finan. Account. 17 (3), 301–318.

Chui, A., Wei, J., 1998. Book-to-market, firm size, and the turn-of-the-year effect: evidence from Pacific-Basin emerging markets. Pacific-Basin Finan. J. 6 (3-4), 275-293.

da Silva Filho, O.C., Ziegelmann, F.A., Dueker, M.J., 2012. Modeling dependence dynamics through copulas with regime switching. Insurance Math. Econ. 50 (3), 346–356.

Darrat, A.F., Li, B., Wu, L., 2012. Revisiting the risk-return relation in the South African stock market. Afr. J. Busi. Manage. 6 (46), 11411-11415.

De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990. Noise trader risk in financial markets. J. Polit. Econ. 98, 703-738.

French, K.R., Schwert, G.W., Stambaugh, R.F., 1987. Expected stock returns and volatility. J. Financ. Econ. 19 (1), 3-30.

Ghysels, E., Santa-Clara, P., Valkanov, R., 2005. There is a risk-return trade-off after all. J. Financ. Econ. 76 (3), 509-548.

Glosten, Lawrence R., Jagannathan, Ravi, Runkle, David E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. J. Finan. 48, 1779–1801.

Guo, H., Whitelaw, R.F., 2006. Uncovering the risk-return relation in the stock market. J. Finance 61 (3), 1433-1463.

Hamilton, J.D., Susmel, R., 1994. Autoregressive conditional heteroskedasticity and changes in regime. J. Econometrics 64 (1–2), 307–333.

Kovačić, Z.J., 2008. Forecasting volatility on the Macedonian Stock Exchange. Int. Res. J. Finan. Econ. 18, 182-212.

Lanne, M., Saikkonen, P., 2003. Modeling the U.S. short-term interest rate by mixture autoregressive processes. J. Financ. Econometr. 1, 96-125.

León Valle, Á., Nave Pineda, J., Rubio Irigoyen, G., 2005. The Relationship between Risk and Expected Return in Europe (No. 201025). Fundacion BBVA/BBVA Foundation.

Li, Q., Yang, J., Cheng, H., Chang, Y.J., 2005. The relationship between stock returns And volatility in international stock markets. J. Empirical Finance 12 (5), 650–665.

Lundblad, C., 2007. The risk-return trade-off in the long-run. J. Financ. Econ. 85, 123–150.

Mandimika, N.Z., Chinzara, Z., 2012. Risk–Return Trade-Off And Behaviour Of Volatility On The South African Stock Market: Evidence From Both Aggregate And Disaggregate Data. South Afr. J. Econ. 80 (3), 345–366.

Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: A new approach. Econometrica 59, 347–370 (1991).

Pástor, L., Sinha, M., Swaminathan, B., 2008. Estimating the intertemporal risk-return Trade-off using the implied cost of capital. J. Finan. 63, 2859–2897.

Paudyal, K., Saldanha, L., 1997. Stock returns and volatility in two regime markets: international evidence. Int. Rev. Financ. Anal. 6 (3), 209-228.

Rapach, D.E., Strauss, J.K., Guofu, Z, 2013. International stock return predictability: whatis the role of the United States? J. Finan. 68, 1633-1662.

Suliman Zakaria Suliman, A., 2012. The Risk-return Trade-off in Emerging Stock Markets: Evidence from Saudi Arabia and Egypt. Int. J. Econ. Finan. 4 (6), 11.

Tabak, B.M. & Guerra, S.M. (2002). Stock returns and volatility. Central do Brasil, working Paper, DEPEP, Rio de Janeiro, available at: www.sbe.org.br/ebe24/060. pdf (accessed May 1).

Tah, K.A., 2013. Relationship between Volatility and Expected Returns in Two Emerging Markets. Busi. Econ. J. 2013. BEJ-84.

Theodossiou, P., Lee, U., 1995. Relationship between volatility and expected returns across international stock markets. J. Busi. Finan. Account. 22, 289-300.

Tiwari, A.K., Abakah, E.J.A., Le, T.L., Leyva-de la Hiz, D.I., 2021. Markovswitching dependence between artificial intelligence and carbon price: The role of policy uncertainty in the era of the 4th industrial revolution and the effect of COVID-19 pandemic. Tech. Forecast. Soc. Change 163, 120434.

Whitelaw, R.F., 1994. Time variations and co-variations in the expectations and volatility of stock market returns. J. Finance 49, 515-541.

Xing, X.J., Howe, J.S., 2003. The empirical relationship between risk and return: evidence from the UK. Int. Rev. Financ. Anal. 12 (3), 329-346.

Yang, M., 2011. Volatility feedback and risk premium in GARCH models with generalized hyperbolic distributions. Stud. Nonlin. Dyn. Econometr. 15 (3), 124–142.