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Asia-Pacific Islamic Stocks and Gold: A Markov-switching Copula Estimation

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This paper tests regime changes of the conditional dependence between Asia-Pacific Islamic stocks and gold. Relying on a time-varying Student's *t* copula with Markov-switching autoregressive conditional heteroskedasticity (MSGARCH), this paper finds the dependence is negative and significant, implying strong diversification benefits. In addition, the copula with MSGARCH is the best-fitting model. Finally, the copula with a single-regime specification consistently outperforms the other models when forecasting value at risk.

I. Introduction

This note tests whether a dynamic Student's *t* copula with Markov-switching autoregressive conditional heteroskedasticity (MSGARCH) recognizes regime changes in the dependence between Asia-Pacific Islamic stocks and gold and outperforms non-MSGARCH models in estimating value at risk (VaR). The responsiveness of Asia-Pacific Islamic stocks to the pandemic has been well documented (Salisu & Sikiru, 2020). However, no conclusive impact of gold in reducing the risk of stock markets during the COVID-19 outbreak is observed. For instance, gold is not a safe haven asset for Chinese equity markets (Corbet et al., 2020). Salisu et al. (2021) find the gold market is able to function as a safe haven. In this spirit, this note captures regime changes to revisit the hedge effectiveness of gold against the risk of Islamic and conventional stock markets.

This paper hypothesizes a negative conditional dependence between Asia-Pacific Islamic stocks and gold in a high-volatility regime. This hypothesis is motivated by the ability of gold to minimize the risk of stocks during the pandemic, which has been well documented (Padhan & Prabheesh, 2021). One limitation of the literature is that mostly non-MSGARCH models are used to measure the hedge effectiveness of gold against the risk of stocks during the pandemic (Ajmi et al., 2021; Corbet et al., 2020; Fakhfekh et al., 2021; Jeribi & Ghorbel, 2021; Sikiru & Salisu, 2021).

This note uses daily time-series data and a regime-switching Student's *t* copula. It concludes that an MSGARCH model with a Student's *t* copula has the best fit. In addition, the dependence between gold and Islamic stocks exhibits tail symmetry. A robustness check (using conventional stocks and gold) shows similar results. The dependence between Islamic stocks and gold on the structural break is lower than for the dependence between conventional stocks and gold, suggesting stronger diversification benefits.

The remainder of the paper is organized as follows. Section II reveals the methodology. Section III presents the main findings. Section IV draws the conclusion.

II. Methodology

This note uses the Dow Jones Islamic Market Asian/Pacific Developed TopCap Index (Asian DJIM) to proxy for Islamic stocks (large- and mid-cap stocks located in developed Asia-Pacific markets. It also utilizes the Dow Jones Composite Average (DJCA), which represents large, well-known U.S. companies for comparison, and exchange-traded funds for gold (GLD). The indexes are retrieved from S&P Global (https://www.spglobal.com/spdji/en/). The whole sample covers from December 7, 2015,[1] to June 30, 2021, and two subsamples respectively cover the pre-COVID-19 pandemic period, from December 7, 2015, to March 10, 2020, and the COVID-19 pandemic period, from March 11, 2020,[2] to June 30, 2021.

This note begins with determining the margin of logarithmic returns by fitting the Glosten–Jaganathan–Runkle (1993) GARCH model, obtaining the standardized residuals, and applying a cumulative distribution function. This research follows Maneejuk & Yamaka (2019) to estimate a dynamic Student's *t* copula, as follows:[3]

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1 December 7, 2015, was the launch date of the DJIM Asian.

2 The World Health Organization announced COVID-19 to be a global pandemic on March 11, 2020.

3 This paper uses the R package DynamicCOP (available at https://rdrr.io/github/woraphonyamaka/DynamicCop/) and finds that a Gauss-

$$\rho_{T,t} = \Delta\, \mathcal{W}_0^T + \mathcal{W}_1^T \rho_{\mathbb{T},t-1} + \mathcal{W}_2^T \frac{1}{10} \sum_{j=1}^{10} \mathcal{F}_1^{-1}(u_{t-j}) \mathcal{F}_1^{-1}(v_{t-j}) \quad (1)$$

The analysis uses a dynamic Student's *t* copula model with regime-switching estimation according to Fei et al. (2017) and Maneejuk & Yamaka (2019), as follows:[4]

$$\rho_{T,t}\mathcal{S}_t = \Delta\, \mathcal{W}_0^T \mathcal{S}_t + \mathcal{W}_1^T \mathcal{S}_t \rho_{\mathbb{T},t-1} + \mathcal{W}_2^T \mathcal{S}_t \frac{1}{10} \sum_{j=1}^{10} \mathcal{F}_1^{-1}(u_{t-j}) \mathcal{F}_1^{-1}(v_{t-j}) \quad (2)$$

A two-regime model is estimated, $\mathcal{S}_t \in \{1,2\}$, where $\mathcal{S}_t$ = 1 denotes a low-volatility regime and $\mathcal{S}_t$ = 2 represents a high-volatility regime. This estimation is used because the volatility predictions of standard GARCH-type models are potentially less capable of extracting the actual volatility in the case of regime changes. This study also evaluates one-day-ahead VaR forecasts (Ardia et al., 2019). A total of 50% of the data are out of sample and estimated by maximum likelihood every 50 observations. The dynamic quintile (DQ) and the conditional coverage (CC) tests determine if the forecasts fit (Christoffersen, 1998; Engle & Manganelli, 2004).

III. Main Findings

Table 1 shows the models exhibit no heteroscedasticity or serial correlation in the estimated standardized residuals, based on Ljung–Box Q-statistics and autoregressive conditional heteroskedasticity statistics, suggesting strong goodness of fit.[5] Moreover, the reaction coefficients are less than 0.1, indicating that volatility is not very sensitive to market events. The γ value is positive and significant for Islamic and conventional stocks, suggesting a leverage effect. This result indicates that negative sentiment has a more significant effect than positive news on conditional variances. All the estimates of $\alpha + \beta$ are above 0.9, implying that shocks in the stock and gold markets have highly persistent volatility.

Table 2 shows the Student's *t* copula with MSGARCH estimation is the best-fitting model due to the lower Akaike information criterion. Therefore, this discussion focuses on models with regimes K= 1 and K = 2. For instance, the $\mathcal{W}_1^T \mathcal{S}_t$ parameters are mostly significant and negative, implying low persistence.

Focusing on the whole sample period, the parameter $\mathcal{W}_2^T \mathcal{S}_t$ is only significant for the two-regime estimation (K = 2) for Islamic stocks and gold, indicating substantial variation. However, the variation parameter $\mathcal{W}_2^T \mathcal{S}_t$ is quite a bit larger than the parameter $\mathcal{W}_1^T \mathcal{S}_t$ in regime K= 1, showing the predominance of dynamic effects.

No predominance of dynamic effects is found for the COVID-19 period. In addition, the variation parameter $\mathcal{W}_2^T \mathcal{S}_t$ is smaller than the persistence parameter $\mathcal{W}_1^T \mathcal{S}_t$ and more significant, implying volatility persists for longer following a turbulent market.

Further, the probability of remaining in the high-volatility regime (P_{22}) is higher for the relation between conventional stocks and gold than for that between Islamic stocks and gold, implying weaker diversification benefits. In addition, P_{11} is highly persistent (above 0.8) during the pandemic.

Figure 1 reveals the time path of the best fitted copula. The conditional dependence between Islamic stocks and gold in the one-regime model ($Ķ = 1$) is higher than the dependence in the two-regime model ($Ķ = 2$), while the increased dependence of the relation between conventional stocks and gold on the structural break implies lower diversification benefits.

In Figure 1A, focus on the dotted vertical lines shows the dependence between gold and Islamic stocks to be decreasing. However, Figure 1B indicates that the dependence between gold and conventional stocks is increasing. This result implies that, in periods of turmoil, gold tends to be a good hedge against the risk of Islamic stocks. This finding is supported by Figure 1C. Finally, the copula with a single-regime specification outperforms the other models when forecasting the VaR, as shown in Table 3.

IV. Conclusion

This paper finds the dependence of Student's *t* copula between stocks and gold to be negative and significant, which indicates tail symmetry. This result reveals the dependence does not emerge during turbulent market events. In addition, the dependence between Islamic stocks and gold is weaker than that between conventional stocks and gold at the structural break, implying greater hedge effectiveness.

Further, the present work shows that the equally weighted portfolio of stocks and gold has lower risk compared to an unhedged strategy during the COVID-19 outbreak. Specifically, gold is more powerful at reducing the risk of Islamic stocks than that of conventional stocks. Moreover, this note finds a time-varying Student's *t*-copula with regime-switching GARCH to be the best-fitting model. This result suggests the predictability of the degree of dependence between stock markets and other commodities can be evaluated by using the fear index as a predictor.

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ian copula does not fit.

4 This note uses the R package MSGARCH (available at https://CRAN.R-project.org/package=MSGARCH; see (Ardia et al., 2019)).

5 The diagnostic tests for the pre-COVID-19 and COVID-19 periods show similar results. Due to limited space, they are not tabulated here.

Table 1. Optimal Parameters

	GOLD	DJIM Asian	DJCA
	Estimate	**Estimate**	**Estimate**
Mu	0.000	0.000	0.000
ar1	0.675***	-132.000***	-0.377***
ar2	0.105***	-0.932***	0.989***
ar3	0.674***		-0.062
ar4	-0.996***		-0.817
ar5	-0.001		
ma1	-0.678***	0.101**	0.354***
ma2	-0.101***	0.933***	-1.024***
ma3	-0.684***		0.051***
ma4	1.008***		0.820***
Ω	0.000	0.000*	0.000***
α(reaction)	0.068***	0.007	0.079***
β(persistence)	0.940***	0.898***	0.817***
γ(leverage)	-0.045***	0.139***	0.171***
Diagnostic tests of non-MSGARCH standardized residuals			
LogLikelihood	4802.920	4683.386	4866.296
Akaike Information Criterion	-6.833	-6.671	-6.925
LB Q(Lag 1)	1.580	0.008	0.906
LB Q(Lag 26)	9.844	2.792	5.434
ARCH Lag(3)	0.019	0.212	0.106
ARCH Lag(5)	0.038	2.951	1.584
Diagnostic tests of MSGARCH standardized residuals			
Regime Ķ = 1			
LB Q(Lag 1)	0.379	2.557	3.100
LB Q(Lag 20)	14.373	22.699	24.104
ARCH Lag(3)	2.526	4.476	4.564
ARCH Lag(5)	2.707	8.051	5.343
Regime Ķ = 2			
LB Q(Lag 1)	0.471	2.564	3.373
LB Q(Lag 20)	14.079	22.691	24.542
ARCH Lag(3)	3.097	4.741	5.183
ARCH Lag(5)	3.113	8.603	5.804

Notes: This table shows optimal parameters of gold, Islamic stocks (Asian DJIM), and conventional stocks (DJCA) fitted by GJR-GARCH, with data from December 7, 2015 to June 30, 2021. Symbols ***, ** & * show statistical significance at the 1%, 5% & 10% levels, respectively. *Mu* is the conditional mean; *ar1* is autoregressive lag 1, *ar2* is autoregressive lag 2, and so on; and *ma1* is the moving average lag 1, *ma2* is moving average lag 2, and so on. The non-MSGARCH standardized residuals are obtained from the GJR-GARCH model (Glosten et al., 1993) while the MSGARCH standardized residuals are retrieved from the Markov Switching-GJR-GARCH (Ardia et al., 2019) model. Finally, LB (Ljung-Box *Q*-statistic) and ARCH test statistics represent serial correlation and heteroscedasticity, respectively.

Table 2. Time-Varying Student-*t* Copula Parameters

	Regime Ķ = 1		Regime Ķ = 2		Non-MSGARCH	
Panel A: Whole Sample (Dec 7, 2015 to Jun 30, 2021)						
	DJIM-GOLD	DJCA-GOLD	DJIM-GOLD	DJCA-GOLD	DJIM-GOLD	DJCA-GOLD
$\mathcal{W}_0^T \mathcal{S}_t$ *(dependence)*	-0.161***	-0.447***	-0.142***	-0.436***	-0.978*	-0.353***
$\mathcal{W}_1^T \mathcal{S}_t$ *(persistence)*	-0.092***	-1.464***	-0.049	-1.439***	-0.141**	-0.111***
$\mathcal{W}_2^T \mathcal{S}_t$ *(variation)*	-0.029	0.208	-0.216***	0.195	-0.111	-0.334***
AIC	-46.131	-52.805	-46.426	-49.448	-40.125	-39.07
LL	29.065	32.402	29.213	30.724	26.062	25.535
Transition Probabilities Matrix						
P_{11}	1.000	1.000	0.796	0.592		
P_{22}			0.777	0.887		
Panel B: Pre-Covid 19 (Dec 7, 2015, to March 10, 2020)						
	Regime Ķ = 1		Regime Ķ = 2		Non-MSGARCH	
	DJIM-GOLD	DJCA-GOLD	DJIM-GOLD	DJCA-GOLD	DJIM-GOLD	DJCA-GOLD
$\mathcal{W}_0^T \mathcal{S}_t$ *(dependence)*	-0.235	-1.055***	-0.828***	-1.063*	-0.139	-0.703***
$\mathcal{W}_1^T \mathcal{S}_t$ *(persistence)*	-0.094***	-0.151***	-0.157**	-0.171***	-0.094***	-0.116***
$\mathcal{W}_2^T \mathcal{S}_t$ *(variation)*	-0.285***	-0.111	-0.126***	-0.116	-0.308***	-0.181***
AIC	-30.352	-28.959	-31.055	-27.757	-30.293	-27.476
LL	21.176	20.479	21.527	19.878	21.146	19.735
Transition Probabilities Matrix						
P_{11}	1.000	1.000	0.953	0.979		
P_{22}			0.682	0.970		
Panel C: Covid-19 (March 11, 2020, to Jun 30, 2021)						
	Regime Ķ = 1		Regime Ķ = 2		Non-MSGARCH	
	DJIM-GOLD	DJCA-GOLD	DJIM-GOLD	DJCA-GOLD	DJIM-GOLD	DJCA-GOLD
$\mathcal{W}_0^T \mathcal{S}_t$ *(dependence)*	-0.194***	-0.432***	-0.246***	-0.559***	-0.307	-0.482
$\mathcal{W}_1^T \mathcal{S}_t$ *(persistence)*	-0.011	-0.607***	-0.019	-0.588***	-0.035	-0.595***
$\mathcal{W}_2^T \mathcal{S}_t$ *(variation)*	-0.562***	-0.719***	-0.662***	-0.612***	0.007	-0.731
AIC	-5.104	-12.758	-6.267	-15.297	-4.616	-12.519
LL	8.552	12.379	9.133	13.648	8.308	12.259
Transition Probabilities Matrix						
P_{11}	1.000	1.000	0.869	0.856		
P_{22}			0.663	0.781		

Notes: This table reports the dynamic Student-*t* copula parameters of gold, Islamic stocks (Asian DJIM), and conventional stocks (DJCA). *LL* is Log Likelihood. *AIC* is Akaike Information Criterion. Symbols ***, ** & * indicate statistical significance at the 1%, 5% & 10% levels, respectively. The data are divided into three samples: Panel A shows whole sample, Panel B represents the pre-COVID-19 period while the COVID-19 period is in Panel C. P_{22} is the probability of staying in a turbulent market while P_{11} is the probability of staying in a tranquil period. Regime K = 1 and Regime K = 2 parameters are estimated following Maneejuk et al. (2021) while the non-MSGARCH parameters are computed following Maneejuk & Yamaka (2019).

Table 3. Accuracy of VaR estimations

	CC			DQ		
	1-regime	2-regime	non-msgarch	1-regime	2-regime	non-msgarch
VaR 5% level						
Islamic Stocks/Gold	0.210	0.875	0.475	0.272	0.504	0.496
Conventional Stocks/Gold	0.112	0.065	0.428	0.358	0.001	0.013
VaR 1% level						
Islamic Stocks/Gold	0.682	0.487	0.010	0.182	0.219	0.009
Conventional Stocks/Gold	0.175	0.035	0.003	0.185	0.000	0.000

Notes: The table shows the p–values of the conditional coverage test (CC) and the dynamic quantile test (DQ) for the one–day ahead VaR of equally-weighted portfolio. The gray-shaded color reports the p–values below the 5% level, indicating VaR forecasts are not fit. 1-regime and 2-regime are fitted by the Markov Switching-GJR-GARCH model while the non-MSGARCH is fitted by the GJR-GARCH model.

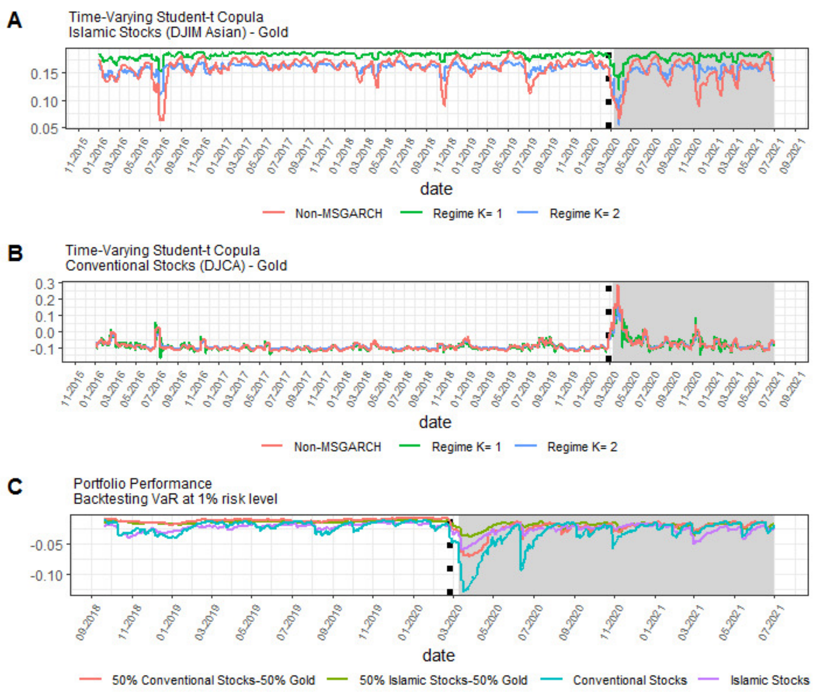

Figure 1. Time path of best fitted dynamic Student-t copula and VaR

Notes: Figure A shows the dynamic dependence of Islamic stocks (Asian DJIM) and gold. Figure B reveals the dynamic dependence of conventional stocks (DJCA) and gold. Figure C indicates VaR at the 1% risk level of equally weighted porfolios, Islamic stocks, and conventional stocks. The dotted vertical lines are the Bai-Perron breakpoints (Bai & Perron, 1998). The shaded area is the COVID-19 period.

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