Peer-reviewed research

Can Tail Risk Predict Asia-Pacific Exchange Rates Out of Sample?

Idris A. Adediran[1][a]

[1] Centre for Econometric and Allied Research, University of Ibadan, Nigeria.

Keywords: meese-rogoff puzzle, asia-pacific, tail risk, forecasting

https://doi.org/10.46557/001c.23501

Asian Economics Letters

Vol. 2, Issue 3, 2021

We present novel evidence to show that tail (market) risk, measured as the conditional autoregressive value at risk, is a good predictor of Asia-Pacific exchange rates. We use daily exchange rate data for the Australian dollar, the Chinese yuan, the Indonesian rupiah, the Japanese yen, the Malaysian ringgit, the New Zealand dollar, the Philippine peso, and the Singapore dollar each against the US dollar, the pound sterling, and the euro between January 3, 2007, and March 8, 2021. Impact analyses suggest hedging benefits for investors in US dollar–denominated exchange rates, especially in advanced Asia-Pacific countries. Superior out-of-sample forecast performance appears to supersede the Meese–Rogoff puzzle.

1. Introduction

This study contributes to the Meese–Rogoff (1983) puzzle, which contends that time-series models cannot outperform autoregressive models in exchange rate out-of-sample predictability. On the contrary, the present study shows that information contained in extreme market events, measured by tail risk, can be exploited to predict the exchange rates for Asia-Pacific (AP) markets.[1] We build on the study of Bouri et al. (2020), who find stronger return spillover among AP currency markets with extreme bands, to situate the contribution of our paper.[2] Further motivation to study the predictive content of tail risk is based on the baseline results that extreme events, such as the 1997–1998 Asian financial crisis and the 2008–2009 global financial crisis, impact the volatility of the foreign currency markets of the AP region (Ahmad et al., 2012; Darrat et al., 2011; Liu & Yang, 2017; Melvin & Taylor, 2009).[3]

Following Bali et al. (2009) in capturing conditional volatility, we seek theoretical backing in the intertemporal capital asset pricing model (see Merton, 1973, 1980) to incorporate tail risk as a measure of market risk. We strengthen our argument with the position that mean-based forecasts of exchange rate returns can be grossly inadequate (Bouri et al., 2020). Hence, we quantify tail risk using Engle and Manganelli's (2004) conditional autoregressive value at risk (CAViaR) method, as well as to forecast AP foreign exchange (forex) market returns. This effort proves worthwhile, since we document strong out-of-sample forecast performances for tail risk across the full sample and advanced countries and emerging countries in the AP region. Following the introduction, next, we present the methodology in Section 2. The discussion of results follows in Section 3, and Section 4 concludes the paper.

2. Methodology

Our analysis has two layers: 1) the specification of the conditional autoregressive quantile models for estimating the AP currency market value at risk and 2) the specification of the predictive model for forecasting AP forex market returns, where we test whether the inclusion of tail risk improves forecast performance over the baseline historical average model.

We adopt the CAViaR (for its computational advantages, see Engle & Manganelli, 2004) in its generic specification

a Corresponding author email: meetadediran@gmail.com; ia.adediran@cear.org.ng

We are grateful to the anonymous reviewer and the editorial team of the Asian Economics Letters for their efforts to improve the quality of the paper. I am also indebted to research fellows at the Centre for Econometric and Allied Research, Ibadan, Nigeria for their invaluable inputs.

1 The choice of the AP region is based on increased financial integration among the countries (Didier et al., 2017).

2 Iyke (2020) and Narayan (2020), for example, have also highlighted the vulnerability of exchange rates to risks associated with the current pandemic.

3 Tail risk has been studied in predictive models for stocks (Li et al., 2021; Van Oordt & Zhou, 2016).

and as specified in the adaptive, symmetric absolute value, asymmetric slope, and indirect generalized autoregressive conditional heteroskedasticity (1,1) variants, respectively:[4]

$$f_t(\beta) = \beta_0 = \sum_{i=1}^{q} \beta_i f_{t-i}(\beta) + \sum_{j=1}^{r} \beta_j l\left(x_{t-i}\right) \quad (1)$$

$$\begin{aligned} f_t\left(\beta_1\right) &= f_{t-1}\left(\beta_1\right) \\ &+ \beta_1 \left\{ \left[1 + \exp\left(G\left[y_{t-1} - f_{t-}\left(\beta_1\right)\right]\right)\right]^{-1} - \theta \right\} \end{aligned} \quad (2)$$

$$f_t(\beta) = \beta_1 + \beta_2 f_{t-1}(\beta) + \beta_3 \left|y_{t-1}\right| \quad (3)$$

$$f_t(\beta) = \beta_1 + \beta_2 f_{t-1}(\beta) + \beta_3 (y_{t-1})^{+} + \beta_4 (y_{t-1})^{-} \quad (4)$$

$$f_t(\beta) = \left(\beta_1 + \beta_2 f_{t-1}^2(\beta) + \beta_3 y_{t-1}^2\right)^{1/2} \quad (5)$$

where $f_t(\beta) = f_t(x_{t-1}, \beta_\theta)$ represents either the 1% or 5% quantile of the distribution of the AP exchange rate returns at time t, formed at $t-1$; $\beta_i f_{t-i}(\beta), \forall i = 1, \ldots, q$ are autoregressive terms; l are lagged observables; and G is constrained to be a positive finite number. We select the optimal model from the four variants of the CAViaR model based on the dynamic quantile (DQ) test and %Hits criteria.

We evaluate the predictive content of the CAViaR series in the return predictability for AP currencies, with, first, a simple time-series specification and, then, a panel specification that accounts for cross-sectional dependence and heterogeneity, amid other salient features (Chudik & Pesaran, 2015; Westerlund & Narayan, 2016), with the following equations, respectively:

$$r_t = \alpha + \theta TR_t + e_t \quad (6)$$

$$\begin{aligned} r_{i,t} &= \omega_i + r_{i,t-1} + \sum \beta_i B_{i,s} + \delta_i TR_{i,t-1} + \varepsilon_{i,t}, \varepsilon_{i,t} \\ &= \lambda_i f_t + v_{i,t} \\ s &= t, \ldots, t - \rho T, i = 1, 2, \ldots N, t = 1, 2, \ldots T \end{aligned} \quad (7)$$

where r_t is the exchange rate return, computed as the logarithmic difference, in percent, of the bilateral exchange rates; TR_t is the measure of tail risk obtained from the three exchange rate series; $\beta_i \neq 0$ is the cross-sectional average; ω_i and δ_i are parameters that differ across the countries; $\varepsilon_{i,t}$ is a two-way error term that captures both factor loadings (λ and f_t); and the remainder error is $v_{i,t}$. We include five lags in Eq. (7) (where $\sum_1^5 \hat{\delta}_i > 0$) and evaluate the significance of the cumulative parameter using F-tests.

We select eight AP countries' currencies:[5] the Australian dollar (AUD), the Chinese yuan (CNY), the Indonesian rupiah (IDR), the Japanese yen (JPY), the Malaysian ringgit (MYR), the New Zealand dollar (NZD), the Philippine peso (PHP), and the Singapore dollar (SGD). For robustness, we use three variants of the exchange rate pairs of domestic currencies against the US dollar (USD), the euro (EUR), and the pound sterling (GBP), obtained at a daily frequency between January 3, 2007, and March 8, 2021.[6] We split the data with a ratio of 75 to 25 between the in- and out-of-sample forecast evaluations, respectively. We use the forecast evaluation measure of Clark & West (2007) to compare the in- and out-of-sample forecasts for the return predictive model containing tail risk against the baseline historical average model.

3. Results

As in the previous section, the results are two-fold. We obtain tail risk as measures of AP forex rate market risks, designated by Engle & Manganelli (2004) as the CAViaR. We produce the CAViaR for both the 1% and 5% tail distributions across the four specifications (see Eqs. (2) to (5)) and select the optimal tail distributions for each country, based mainly on the statistical nonsignificance of the DQ test (see Table 1).[7] We then adopt the panel data technique of Chudik & Pesaran (2015) to evaluate the predictive power of the optimal tail risk in the model for the AP forex market returns, with results for advanced and emerging countries, as well as for the full sample. The choice of the panel technique is not driven by the desire to save space, but, rather, by evidence of strong financial integration in the region, especially because of extreme market events (Ahmad et al., 2012; Darrat et al., 2011; Didier et al., 2017; Liu & Yang, 2017).[8]

The impact analysis results in Table 2, Panel A indicate that market (tail) risk significantly impacts AP forex markets for USD- and GBP-denominated exchange rate returns. In terms of the sign, while the impacts of tail risk are generally positive for USD-denominated exchange rates (and statistically significant for the full sample and advanced countries' panel), it is negative for GBP-denominated exchange rates across panels. The results for the euro-denominated exchange rate returns are neither significant nor consistent. These findings reveal notable inferences for investors in AP forex markets. The implication is that investors could use USD-denominated exchange rates to hedge against GBP- and EUR-denominated exchange rates, especially in advanced AP markets.

We compare the forecast accuracy of the exchange rate return model containing market risk as a predictor with the baseline using only a constant as the predictor (historical average model).[9] We evaluate the in- and out-of-sample

4 This approach has been employed to measure stocks tail risks (Salisu, Gupta, & Ogbonna, 2021); and oil tail risk (Salisu, Gupta, & Ji, 2021).

5 See https://worldpopulationreview.com/country-rankings/apac-countries.

6 Data are from the Bank for International Settlements (https://www.bis.org/cbanks.htm) or, if not found there, from investing.com.

7 Prior to this, we document the summary statistics for each of the exchange rate return series. We present the trends of the exchange rate returns with the optimal tail risk series in Figure 1. We limit the results to USD exchange rate pairs, given space constraints.

8 Nonetheless, the estimation technique accounts for any potential heterogeneity effects in the relations among the countries.

9 Note that this is the equivalent of the autoregressive model if the exchange rate model were expressed as prices. The autoregressive terms are dropped from the right-hand side, leaving only the constant after the prices are expressed in the form of returns, thereby reducing the baseline model to a historical average model.

Table 1: Preliminary results

Panel A: Summary statistics						
	USD		GBP		EUR	
	Mean	SD	Mean	SD	Mean	SD
AUD	-0.0020	0.8256	-0.0114	0.7127	-0.0064	0.6901
CNY	-0.0050	0.1767	0.0110	0.5831	-0.0110	0.5916
IDR	0.0148	0.5682	0.0044	0.7096	0.0131	0.6777
JPY	-0.0053	0.6490	-0.0127	0.8661	-0.0096	0.7709
MYR	0.0074	0.4174	-0.0047	0.6212	0.0022	0.5462
NZD	-0.0009	0.8633	-0.0083	0.7389	-0.0032	0.7120
PHP	-0.0002	0.3750	-0.0086	0.6523	-0.0054	0.6353
SGD	-0.0019	0.3498	-0.0110	0.5274	-0.0076	0.4565

Panel B: Optimal tail risks							
Country (Model)		Beta1	Prob.	RQ	%Hits out-	DQ in-(Prob.)	DQ out-(Prob.)
Australia (1% Symmetric)	EUR	0.1304	0.0000	53.5051	0.7168	0.9203	0.7337
	GBP	0.0823	0.0000	59.1123	1.4337	0.4524	0.0624
	USD	0.0572	0.0160	58.4777	0.8961	0.9484	0.1282
China (1% Indirect GARCH)	EUR	0.0218	0.1342	52.8522	0.1439	0.9181	0.5256
	GBP	0.8530	0.0000	47.1172	1.8705	0.6542	0.0369
	USD	0.0000	0.2998	13.9971	0.8633	0.6823	0.9249
Indonesia (1% Asymmetric)	EUR	0.0229	0.1608	62.4892	0.6356	0.9143	0.9332
	GBP	0.0354	0.1035	65.7241	0.6356	0.0257	0.9936
	USD	0.1608	0.0181	48.5774	1.0593	0.6010	0.9992
Japan (1% Asymmetric)	EUR	0.0326	0.0487	80.3189	0.4286	0.9120	0.8822
	GBP	0.0282	0.0002	89.9377	0.7143	0.7049	0.9952
	USD	0.1054	0.0002	64.7149	0.5714	0.7645	0.9117
Malaysia (5% Indirect GARCH)	EUR	0.0046	0.0726	185.1137	4.1237	0.6540	0.5320
	GBP	0.0038	0.1606	201.8054	4.7423	0.7766	0.2403
	USD	0.0070	0.0092	139.2723	3.5052	0.2823	0.4601
New Zealand (5% Indirect GARCH)	EUR	0.0032	0.1872	214.5715	4.0925	0.9165	0.2952
	GBP	0.0069	0.0440	229.9151	4.4484	0.4491	0.5857
	USD	0.0091	0.0965	251.4171	4.8043	0.1105	0.5935
Philippines (5% Indirect GARCH)	EUR	0.0032	0.1872	214.5715	4.0925	0.9165	0.2952
	GBP	0.0069	0.0440	229.9151	4.4484	0.4491	0.5857
	USD	0.0091	0.0965	251.4171	4.8043	0.1105	0.5935
Singapore (5% Asymmetric)	EUR	0.0142	0.0082	148.4003	3.0000	0.9145	0.1278
	GBP	0.0095	0.0159	171.2783	4.1429	0.5819	0.4738
	USD	0.0038	0.0669	114.1436	3.2857	0.1818	0.2560

Notes: In Panel A, SD represents standard deviation and NOBS stands for number of observations. In Panel B, we select the optimal tail risk series across the four variants of CAViaR models based on the DQ test and %Hits (see Engle & Manganelli, 2004 for full details). Given space constraints, we suppress the results for Beta2 to Beta4.

forecast performance of these models across the full sample and the advanced and emerging countries' panels, respectively. Hence, we divide the data sample along a 75-to-25 ratio and evaluate the out-of-sample forecast for two out-of-sample horizons (h = 10 and h = 20). The Clark–West statistic proves handy in this direction, and we expect it to be statistically significant, in which case, the extended model is preferred.

The in- and out-of-sample forecast evaluation results are presented in Table 2, Panels B and C, respectively. In

Table 2: Predictability and forecast evaluation results

	USD	GBP	EUR
Panel A: predictability results			
Full sample	0.0146*	-0.0312***	0.00331
	[0.0693]	[0.0002]	[0.7409]
Advanced countries	0.0095**	-0.0270***	0.00024
	[0.0170]	[0.0022]	[0.9865]
Emerging countries	0.01378	-0.0327*	-0.0020
	[0.1946]	[0.0454]	[0.8220]
Panel B: In-sample forecast evaluation			
Full sample	0.0028***	0.0033***	0.00203***
	(0.00064)	(0.00074)	(0.00047)
Advanced countries	0.0046***	0.0029***	0.0020***
	(0.00129)	(0.00092)	(0.00078)
Emerging countries	0.0012***	0.0030***	0.0018***
	(0.00042)	(0.00093)	(0.00049)
Panel C: Out-of-sample forecast evaluation			
Full sample *(h=10)*	0.0028***	0.0033***	0.00200***
	(0.00064)	(0.00073)	(0.00046)
Full sample *(h=20)*	0.0028***	0.0032***	0.00201***
	(0.00063)	(0.00073)	(0.00046)
Advanced countries *(h=10)*	0.0046***	0.00290***	0.0020***
	(0.00128)	(0.00092)	(0.00078)
Emerging countries *(h=10)*	0.0012***	0.00295***	0.00177***
	(0.00042)	(0 00093)	(0.00049)

Notes: Values in square brackets are *p*-values of the *F*-test while standard errors are in parenthesis. The forecast evaluation compares the historical average with the model where tail risk is the predictor based on the Clark-West measure. The symbols ***,**,* signify 1%, 5%, and 10% levels of significance respectively.

Panel B, the three models for the exchange rate returns fulfill the conditions, indicating that the model with tail risk outperforms the baseline for in-sample evaluation across the three panels).[10] All the coefficients are significant at the 1% level. The major focus of our study is an out-of-sample forecast evaluation that seeks to challenge the position of Meese & Rogoff (1983) with evidence that AP forex market risk can forecast exchange rate returns out of sample better than the historical average (equivalent to a random walk model without differencing). Our preferred model consistently outperforms the baseline in out-of-sample forecast evaluations across the three variants of exchange rate pairs and the 10- and 20-day-ahead forecast horizons (see Panel C). Interestingly, out-of-sample forecast performance does not wane at longer forecast horizons or depending on whether we consider the full sample or the panels for advanced and emerging AP countries.

4. Conclusion

We build on the work of Bouri et al. (2020), who suggest that return and volatility transmission is heightened among AP currency markets in the extreme tails of conditional distributions. We are also informed by the fact that extreme market events influence the financial climate of the region, as shown by Didier et al. (2017) and Liu & Yang (2017), among others. We improve on these ideas to obtain measures of market risk from the CAViaR of Engle & Manganelli (2004). We test the performance of the CAViaR in a predictive model for the exchange rate returns of eight AP countries, following Chudik and Pesaran's (2015) panel technique. The results clearly show that tail risk matters in predicting exchange rates out of sample, a finding that suggests reconsideration of the Meese–Rogoff puzzle. For investment decisions, we infer that investors in the AP region could obtain hedging benefits in the USD-denominated exchange rate markets of advanced AP countries. In all, there could be a need for a stronger forex buffer (foreign reserves), especially among emerging AP countries, to counter forex market risks.

Submitted: April 10, 2021 AEST. Accepted: April 21, 2021 AEST. Published: June 30, 2021 AEST.

10 Narayan et al. (2020) also show better predictability of their proposed model over the random walk model.

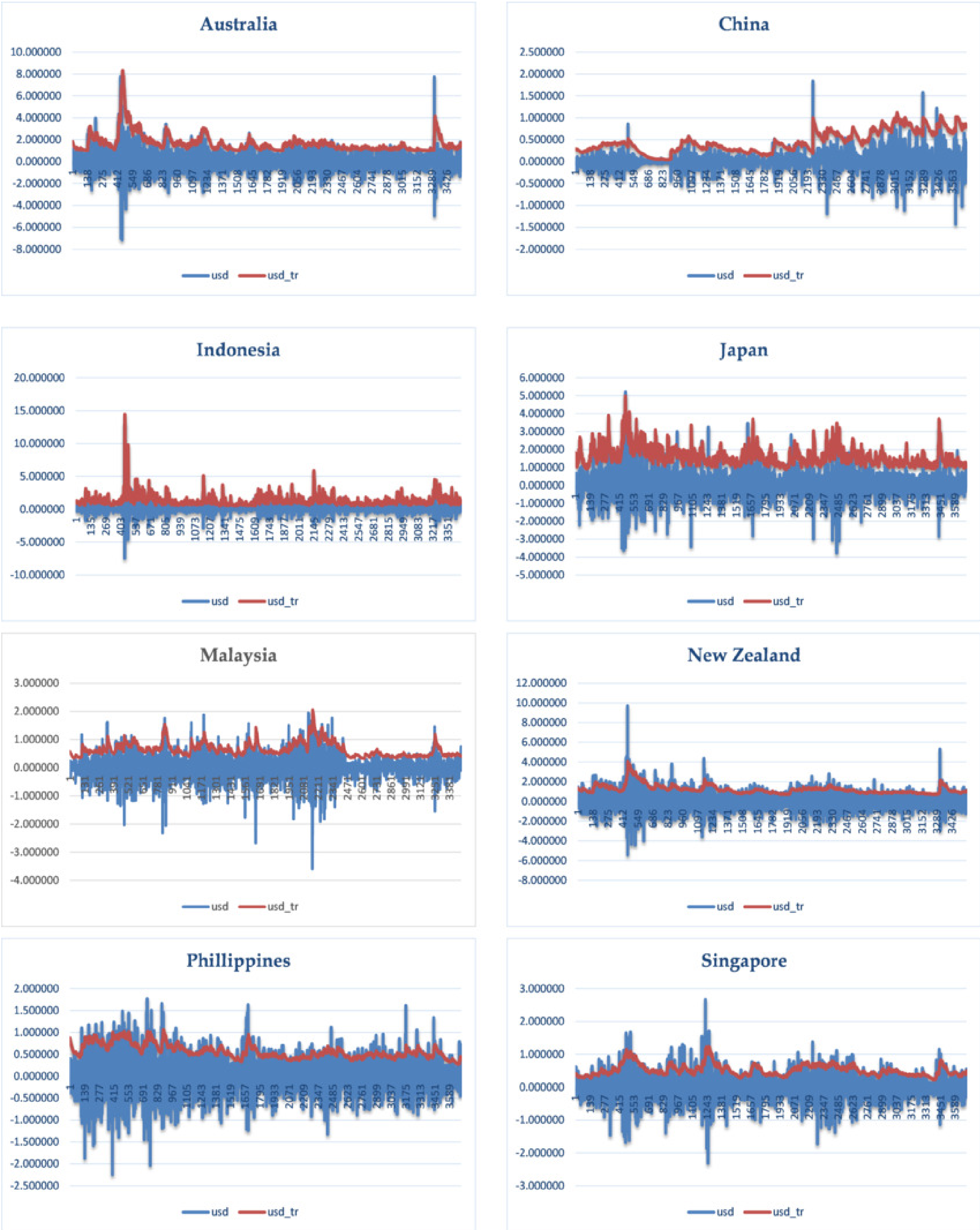

Figure 1: Exchange rate returns and tail risk

Note: The description is limited to the USD exchange rates given space constraints. The rest are available on request.

References

Ahmad, R., Rhee, S. G., & Wong, Y. M. (2012). Foreign exchange market efficiency under recent crises: Asia-Pacific focus. *Journal of International Money and Finance*, *31*, 1574–1592.

Bali, T. G., Demirtas, K., & Levy, H. (2009). Is there an intertermporal relation between downside risk and expected returns? *J Fin Quant Anal*, *44*, 883–909.

Bouri, E., Lucey, B., Saeed, T., & Vo, X. V. (2020). Extreme spillovers across Asian-Pacific currencies: A quantile-based analysis. *International Review of Financial Analysis*, *72*, 101605.

Chudik, A., & Pesaran, M. H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics*, *188*(2), 393–420.

Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, *138*, 291–311.

Darrat, A. F., Gilley, O. W., Li, B., & Wu, Y. (2011). Revisiting the risk/return relations in the Asian Pacific markets: New evidence from alternative models. *Journal of Business Research*, *64*, 199–206.

Didier, T., Llovet, R., & Schmukler, S. L. (2017). International financial integration of East Asia and Pacific. *J. Japanese Int. Economies*, *44*, 52–66.

Engle, R. F., & Manganelli, S. (2004). CAViaR: Conditional Autoregressive Value at Risk by Regression Quantiles. *Journal of Business & Economic Statistics*, *22*(4), 367–381. https://doi.org/10.1198/073500104000000370

Iyke, B. N. (2020). The disease outbreak channel of exchange rate return predictability: Evidence from COVID-19. *Emerging Markets Finance and Trade*, *56*(10), 2277–2297. https://doi.org/10.1080/1540496x.2020.1784718

Li, P., Guo, Y., & Li, A. (2021). Tail risk contagion between international financial markets during COVID-19 pandemic. *International Review of Financial Analysis*, *73*, 101649.

Liu, C., & Yang, H. (2017). Systemic risk in carry-trade portfolios. *Finance Research Letters*, *20*, 40–46.

Meese, R., & Rogoff, K. (1983). Empirical exchange rate models of the seventies: do they fit out of sample? *Journal of International Economics*, *14*, 3–24.

Melvin, M., & Taylor, M. P. (2009). The crisis in the foreign exchange market. *Journal of International Money and Finance*, *28*(8), 1317–1330. https://doi.org/10.1016/j.jimonfin.2009.08.006

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica*, *41*, 867–887.

Merton, R. C. (1980). On estimating the expected return on the market. *J Fin Econ*, *8*, 323–361.

Narayan, P. K. (2020). Has COVID-19 changed exchange rate resistance to shocks? *Asian Economics Letters*, *1*(1), 17389. https://doi.org/10.46557/001c.17389

Narayan, P. K., Sharma, S. S., Phan, D. H. B., & Liu, G. (2020). Predicting exchange rate returns. *Emerging Markets Review*, *42*, 100668. https://doi.org/10.1016/j.ememar.2019.100668

Salisu, A. A., Gupta, R., & Ji, Q. (2021). *Forecasting Oil Price over 150 Years: The Role of Tail Risks* (Working Papers 202120). University of Pretoria, Department of Economics.

Salisu, A. A., Gupta, R., & Ogbonna, A. E. (2021). *Tail Risks and Forecastability of Stock Returns of Advanced Economies: Evidence from Centuries of Data* (Working Papers 202117). University of Pretoria, Department of Economics.

Van Oordt, M. R. C., & Zhou, C. (2016). Systematic tail risk. *Journal of Financial and Quantitative Analysis*, *51*(2), 685–705. https://doi.org/10.1017/s0022109016000193

Westerlund, J., & Narayan, P. (2016). Testing for predictability in panels of any time series dimension. *International Journal of Forecasting*, *32*(4), 1162–1177. https://doi.org/10.1016/j.ijforecast.2016.02.009