APAEA

Salisu, A. A., Lasisi, L., & Olaniran, A. (2021). Do Epidemics and Pandemics Have Predictive Content for Exchange Rate Movements? Evidence for Asian Economies. *Asian Economics Letters*, *2*(3).

Peer-reviewed research

Do Epidemics and Pandemics Have Predictive Content for Exchange Rate Movements? Evidence for Asian Economies

Afees A. Salisu[1] [a], Lukman Lasisi[1], Abeeb Olaniran[1]

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

Keywords: exchange rates, predictability, forecast evaluation, uncertainty

https://doi.org/10.46557/001c.23423

Asian Economics Letters

Vol. 2, Issue 3, 2021

In this paper, we examine the predictive content of uncertainty due to pandemics and epidemics (*UPE*) for the exchange rate movements of selected Asian economies. Our results show evidence of superior out-of-sample predictability of a *UPE*-based predictive model over the benchmark model. Nonetheless, the predictability of *UPE* is stronger before the COVID-19 pandemic than it is after the outbreak and the resilience of the Asian economies to *UPE* is mixed.

I. Introduction

In this paper, we examine the predictive content of uncertainty due to epidemics and pandemics (*UPE*) for exchange rate movements. Restrictions during epidemics and pandemics limit the movement of labour, goods and services and, by extension, cause instabilities in exchange movements (see Narayan, 2020b, 2020c). A few related studies (see Iyke, 2020b; Narayan, 2020b, 2020c; Narayan et al., 2020)[1] offer a pointer in this regard albeit with a focus on in-sample predictability which does not necessarily translate into improved out-of-sample predictability. Thus, our main contribution to the literature involves assessing both the in-sample and out-of-sample forecasts of the *UPE*. Improved out-of-sample forecasts of exchange rates are crucial for monetary policy effectiveness, particularly in terms of minimizing exchange rate risk with associated favorable effects on capital inflows. The connection between the *UPE* and exchange rate hinges on the risk-return hypothesis (such as the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT)), which assumes that financial assets respond to systematic (undiversifiable or market) risk (see Iyke & Ho, 2021). We follow the procedure of Salisu & Adediran (2020) and Salisu & Sikiru (2020), where the *UPE* serves as a predictor,[2] while we employ the approach of Westerlund & Narayan (2012, 2015) to analyze the model. We utilize the new *UPE* dataset by Baker et al. (2020), which covers all the known epidemics and pandemics and comparatively evaluate its predictive ability relative to a benchmark model that ignores the *UPE* variable. Our choice of Asia is underscored by its increasing integration in the global trade—a trade that has declined due to the stringent actions aimed at curtailing the spread of and the COVID-19 pandemic.

Following our experiment with the new dataset, we report results that further advance the literature on exchange rate forecasting. We find evidence that lends support to the inclusion of *UPE* in a predictive model of exchange rate for improved out-of-sample forecasts while the currency movements seem tolerant to COVID-19 in selected countries. Further analyses also show evidence of out-of-sample predictability. Following this section, the rest of the paper is structured as follows: Section II is about data and methodology; Section III has results and discussion; and Section IV contains concluding remarks.

II. Data and Methodology

This study utilizes daily exchange rates of nine Asian economies,[3] using US dollars as the reference currency,[4] alongside the *UPE* data. Our data span the period 30/01/2006 to 29/01/2021 and the analysis covers both the full

a Corresponding author email: adebare1@yahoo.com

Helpful comments from a referee of this journal are acknowledged.

1 Quite a number of papers have also evaluated the relationship between the COVID-19 pandemic and other macro-economic variables, such as stock returns (Haroon & Rizvi, 2020; Salisu & Sikiru, 2020), oil returns (Devpura & Narayan, 2020; Fu & Shen, 2020; Iyke, 2020a; Narayan, 2020a; Prabheesh et al., 2020) and cryptocurrency (Lahmiri & Bekiros, 2020; Mnif et al., 2020).

2 Note that these studies differ in terms of the predicted series. For instance, Salisu & Adediran (2020) consider energy volatility while Salisu & Sikiru (2020) focus on Islamic stocks.

3 Namely: China, Hong Kong, India, Indonesia, Japan, Malaysia, New Zealand, Philippines, Singapore, South Korea, Sri Lanka and Thailand. We consider Asian countries with managed floating exchange rate regime.

4 This data is sourced from https://fred.stlouisfed.org/

sample and the COVID-19 sample (01/01/2020 to 29/01/2021) to capture the impact of the current pandemic specifically on the exchange rate movements. We also include as control variables: (1) oil price, which is the West Texas Intermediate (WTI) crude oil price following the literature (Narayan et al., 2008; Salisu, Cuñado, et al., 2020; Salisu & Mobolaji, 2013; Sharma et al., 2019); and (2) the COVID-19 variable (Iyke, 2020b; Narayan, 2020b, 2020c; Narayan et al., 2020; Salisu & Adediran, 2020). We follow the estimation procedure of Westerlund & Narayan (2012, 2015)[5] with the specification given as:

$$\begin{aligned} er_t = \alpha + \sum_{i=1}^{5} \beta_i^{adj} UPE_{t-i} \\ + \varphi(UPE_t - \rho_o UPE_{t-1}) \\ + \psi Oil_{t-1} + e_t \end{aligned} \quad (1)$$

where er is the series to be predicted and is measured as log return of exchange rate; α is the intercept; *UPE* is the predictor series using the Baker et al. (2020) uncertainty index due to infectious diseases; Oil is the log of WTI crude oil price; and e_t is the zero mean idiosyncratic error term. The coefficient β_i^{adj} is adjusted to capture any inherent persistence effect in the model and measures the impact of the *UPE* on the exchange rate returns.[6] We allow for a maximum of five lags in order to capture more dynamics in the estimation process. Therefore, the underlying null hypothesis of no predictability involves a joint (Wald) test as: $\sum_{i=1}^{5} \beta_i^{adj} = 0$, where the exchange rate is expected to increase with the pandemic if $\sum_{i=1}^{5} \beta_i^{adj} \geq 0$ or shred its value during the pandemic if $\sum_{i=1}^{5} \beta_i^{adj} < 0$ (Salisu, Raheem, et al., 2020; Salisu & Sikiru, 2020). The additional term $\varphi(UPE_t - \rho_o UPE_{t-1})$ corrects for any endogeneity bias resulting from the correlation between the UPE_t and e_t, as well as any inherent unit root problem in the UPE_t. Finally, we pre-weight all the data with the inverse of the standard deviation obtained from a typical GARCH-type model and thereafter estimate the resulting equation with the OLS.

We complete the analysis with the evaluation of the *UPE*-based model in improving the accuracy of exchange rate returns relative to the historical average (constant returns) model that disregards the *UPE* while the 75:25 data split is used for the in-and-out-of-sample forecast evaluations with multiple out-of-sample forecast horizons of 10, 20 and 30 days. We employ the pair-wise forecast measure of Clark & West (2007) test to compare the forecast performance. It follows that the rejection of the null hypothesis suggests that the *UPE*-based model for exchange rate movements outperforms the benchmark model.

III. Main Findings

We begin the discussion of results with the predictability of exchange rate movements for selected Asian economies across three periods (Pre-COVID-19, COVID-19 and full sample periods). Our findings, as contained in Table 1, show that, in the pre-COVID-19 period, the *UPE* is a good predictor of the exchange rate movements in virtually all the nine countries except China given the evidence of statistically significant relationship between the two variables. The relationship is positive for China, India, Japan, Singapore, South Korea, Sri Lanka, and Thailand, implying some resilience of these economies to uncertainty due to pandemics and epidemics. The relationship is, however, negative for Hong Kong and Malaysia, suggesting their vulnerability to the *UPE* during the pre-COVID-19 period. The resilience seems to decline after the announcement of the current pandemic as some countries that were resilient before the pandemic, such as China, India, Japan, and Singapore, are found to be vulnerable during the pandemic. This is expected because these countries, especially China, India, and Japan, have large trading partnerships with Africa, America and Europe whose economies were adversely affected by the current pandemic. Thus, the incidence of the current pandemic contributes to the observed volatility in exchange rates of some Asian economies (see also, Narayan, 2020b, 2020c). However, South Korea, Sri Lanka and Thailand still retain their resilience while the opposite is the case for Hong Kong and Malaysia. Overall (using the full sample), about 60% of countries show some resilience to the *UPE* while 40% of countries (China, Hong Kong, Malaysia, and South Korea) seem vulnerable to it.

Moreover, the in-sample forecast evaluation results in Table 2 show that in the pre-COVID-19 period, our proposed model outperforms the benchmark model for all the countries. The forecast efficiency of the *UPE*-based model slightly declines during the COVID-19 period relative to the period before it as the historical average model outperforms the proposed model for Thailand, China and Sri Lanka. In general, the proposed model outperforms the benchmark model for all the nine countries, contrary to the result of Chen et al. (2010) and Ferraro et al. (2015).

IV. Conclusion

We test the predictive contents of uncertainty due to pandemics and epidemics for exchange rate movements for nine Asian countries, covering the period before and during the current pandemic (COVID-19). On the average, the predictability of *UPE* is stronger before the COVID-19 pandemic than it is after the outbreak. The vulnerabilities of the considered exchange rates are mixed: some countries became vulnerable after the outbreak of COVID-19 while the opposite is the case for others. On the whole, including the *UPE* in the predictive model of exchange rate movements offers better out-of-sample forecast outcomes compared to the benchmark constant returns model.

---

5 Some preliminary tests conducted whose results are suppressed due to space constraints validate our choice of the Westerlund & Narayan (2012, 2015) approach. Both the predicted and predictor series exhibit persistence, conditional heteroscedasticity and serial correlation effects, which are considered salient features that motivate the Westerlund Narayan estimator.

6 The original model is given as $er_t = \alpha + \beta UPE_{t-1} + \psi Oil_{t-1} + \mu_t$ and some computational procedures, as documented in Westerlund & Narayan (2012, 2015), produce the predictive model as specified in Equation (1).

Table 1: Vulnerability and predictability results

	China	Hong-Kong	India	Japan	Malaysia	Singapore	South Korea	Sri Lanka	Thailand
	Pre-COVID-19 sample (1/30/2006 - 12/31/2019)								
UPE	9.08E-06	-0.0006[a]	0.0163[a]	0.022[a]	-0.0028[a]	0.0103[a]	0.0214[a]	0.0015[a]	0.0049[a]
	[0.0014]	[131.9939]	[130.7655]	[16.2329]	[8.0262]	[19.5120]	[28.5919]	[67.0820]	[25.5523]
Nobs	3632	3632	3632	3632	3632	3632	3632	3632	3632
	COVID-19 sample (1/1/2020 - 1/29/2021)								
	China	Hong-Kong	India	Japan	Malaysia	Singapore	South Korea	Sri Lanka	Thailand
UPE	-0.0024[a]	6.64E-05[a]	-0.0022[c]	-0.0032[b]	0.0003	-0.0015	0.0015	0.0072[a]	0.0036[a]
	[18.9797]	[11.6602]	[3.3590]	[4.7377]	[1.2017]	[2.5525]	[2.4037]	[128.1038]	[64.1387]
Nobs	283	283	283	283	283	283	283	283	283
	Full sample (1/30/2006 -1/29/2021)								
	China	Hong-Kong	India	Japan	Malaysia	Singapore	South Korea	Sri Lanka	Thailand
UPE	-0.0008[a]	-9.77E-06	0.0007[a]	0.0007[a]	-2.90E-05	0.0006[b]	-0.0004	0.0033[a]	0.0005[a]
	[47.4840]	[1.7295]	[19.3837]	[12.1969]	[0.0594]	[6.3956]	[1.6684]	[873.5247]	[16.2675]
Nobs	3915	3915	3915	3915	3915	3915	3915	3915	3915

This table shows the vulnerability and predictability results. *UPE* denotes uncertainty due to pandemics and epidemics and it is used to represent Equity Market Volatility: Infectious Disease Tracker, Index as developed by Baker et al. (2020). Values in square brackets represent *F*-statistic. Nobs is the number of observations. Finally, [a], [b] and [c] represent 1%, 5% and 10% significance levels, respectively.

Table 2: Out-of-sample forecast evaluation results

	Pre-COVID-19 (1/30/2006 - 12/31/2019)			COVID-19 (1/1/2020 - 1/29/2021)			Full sample (1/30/2006 -1/29/2021)		
	h = 10	**h = 20**	**h = 30**	**h = 10**	**h = 20**	**h = 30**	**h = 10**	**h = 20**	**h = 30**
China	0.000453^{a}	0.000453^{a}	0.000452^{a}	0.00297	0.003137	0.003046	0.000505^{a}	0.000503^{a}	0.000502^{a}
	(5.206)	(5.228)	(5.226)	(1.419)	(1.549)	(1.566)	(5.354)	(5.355)	(5.350)
Hong Kong	0.0000037^{c}	0.00000368^{c}	0.00000366^{c}	0.0000588^{b}	0.0000576^{c}	0.0000561^{b}	0.00000305^{c}	0.00000309^{c}	0.00000307^{c}
	(1.903)	(1.903)	(1.898)	(2.225)	(2.272)	(2.308)	(1.578)	(1.603)	(1.599)
India	0.020841^{a}	0.020777^{a}	0.020737^{a}	0.00278^{c}	0.001933^{c}	0.001462^{c}	0.018764^{a}	0.018684^{a}	0.018624^{a}
	(7.772)	(7.775)	(7.788)	(0.434)	(0.308)	(0.242)	(7.904)	(7.896)	(7.897)
Japan	0.00914^{a}	0.009079^{a}	0.009023^{a}	-0.001043^{c}	-0.000668^{c}	-0.000884^{c}	0.013403^{a}	0.013307^{a}	0.01325^{a}
	(3.620)	(3.608)	(3.599)	(-0.110)	(-0.073)	(-0.101)	(4.198)	(4.181)	(4.177)
Malaysia	0.008349^{a}	0.008357^{a}	0.008349^{a}	0.005847^{c}	0.00569^{b}	0.005319^{b}	0.007831^{a}	0.0078^{a}	0.007773^{a}
	(7.116)	(7.144)	(7.159)	(2.094)	(2.115)	(2.053)	(7.364)	(7.359)	(7.358)
Singapore	0.022872^{a}	0.022832^{a}	0.022821^{a}	0.004417^{b}	0.004656^{b}	0.004162^{b}	0.021124^{a}	0.021052^{a}	0.02103^{a}
	(11.617)	(11.634)	(11.669)	(0.835)	(0.917)	(0.854)	(11.752)	(11.747)	(11.774)
South Korea	0.022061^{a}	0.02205^{a}	0.022108^{a}	0.006703^{b}	0.007087^{b}	0.006906^{b}	0.022005^{a}	0.021917^{a}	0.021856^{a}
	(4.404a)	(4.417)	(4.444)	(0.817)	(0.900)	(0.913)	(4.520)	(4.517)	(4.519)
Sri Lanka	0.0000533^{c}	0.0000558^{c}	0.0000524^{c}	0.004772	0.00462	0.004881	0.0000851^{c}	0.0000822^{c}	0.0000807^{c}
	(0.332)	(0.349)	(0.329)	(1.136)	(1.148)	(1.261)	(0.537)	(0.520)	(0.513)
Thailand	0.004901^{a}	0.004867^{a}	0.00487^{a}	0.007362	0.007092	0.006237	0.004606^{a}	0.0046^{a}	0.004593^{a}
	(6.083)	(6.059)	(6.084)	(1.589)	(1.599)	(1.456)	(6.164)	(6.176)	(6.187)
Nobs	3642	3652	3662	293	303	313	3925	3935	3945

This table shows the out-of-sample forecast evaluation results. Nobs is the number of observations. The symbols $^{a, b}$ and ^{c} represent 1%, 5% and 10% significance levels, respectively. Values reported in parenthesis are the *t*-statistics. For the Clark and West test, the null hypothesis of a zero coefficient is rejected if this statistic is greater than +1.282 (for a one sided 0.10 test), +1.645 (for a one sided 0.05 test), and +2.00 for 0.01 test (for a one-sided 0.01 test) (see Clark & West, 2007).

Submitted: February 23, 2021 AEST, Accepted: March 10, 2021 AEST

REFERENCES

Baker, S. R., Bloom, N., Davis, S. J., & Terry, S. J. (2020). *Covid-induced economic uncertainty (No. w26983)*. National Bureau of Economic Research. https://doi.org/10.3386/w26983

Chen, Y.-C., Rogoff, K. S., & Rossi, B. (2010). Can exchange rates forecast commodity prices? *Quarterly Journal of Economics*, *125*(3), 1145–1194. https://doi.org/10.1162/qjec.2010.125.3.1145

Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, *138*(1), 291–311. https://doi.org/10.1016/j.jeconom.2006.05.023

Devpura, N., & Narayan, P. K. (2020). Hourly oil price volatility: The role of COVID-19. *Energy Research Letters*, *1*(2). https://doi.org/10.46557/001c.13683

Ferraro, D., Rogoff, K., & Rossi, B. (2015). Can oil prices forecast exchange rates? An empirical analysis of the relationship between commodity prices and exchange rates. *Journal of International Money and Finance*, *54*, 116–141. https://doi.org/10.1016/j.jimonfin.2015.03.001

Fu, M., & Shen, H. (2020). COVID-19 and corporate performance in the energy industry. *Energy Research Letters*, *1*(1). https://doi.org/10.46557/001c.12967

Haroon, O., & Rizvi, S. A. R. (2020). Flatten the curve and stock market liquidity—An Inquiry into emerging economies. *Emerging Markets Finance and Trade*, *56*(10), 2151–2161. https://doi.org/10.1080/1540496x.2020.1784716

Iyke, B. N. (2020a). COVID-19: The reaction of US oil and gas producers to the pandemic. *Energy Research Letters*, *1*(2), 13912. https://doi.org/10.46557/001c.13912

Iyke, B. N. (2020b). 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

Iyke, B. N., & Ho, S.-Y. (2021). Exchange rate exposure in the South African stock market before and during the COVID-19 pandemic. *Finance Research Letters*, *102000*. https://doi.org/10.1016/j.frl.2021.102000

Lahmiri, S., & Bekiros, S. (2020). The impact of COVID-19 pandemic upon stability and sequential irregularity of equity and cryptocurrency markets. *Chaos, Solitons & Fractals*, *138*, 109936. https://doi.org/10.1016/j.chaos.2020.109936

Mnif, E., Jarboui, A., & Mouakhar, K. (2020). How the cryptocurrency market has performed during COVID 19? A multifractal analysis. *Finance Research Letters*, *36*, 101647. https://doi.org/10.1016/j.frl.2020.101647

Narayan, P. K. (2020a). Oil price news and COVID-19—Is there any connection? *Energy Research Letters*, *1*(1), 13176. https://doi.org/10.46557/001c.13176

Narayan, P. K. (2020b). 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. (2020c). Did Bubble Activity Intensify During COVID-19? *Asian Economics Letters*, *1*(2). https://doi.org/10.46557/001c.17654

Narayan, P. K., Devpura, N., & Wang, H. (2020). Japanese currency and stock market—What happened during the COVID-19 pandemic? *Economic Analysis and Policy*, *68*, 191–198. https://doi.org/10.1016/j.eap.2020.09.014

Narayan, P. K., Narayan, S., & Prasad, A. (2008). Understanding the oil price-exchange rate nexus for the Fiji islands. *Energy Economics*, *30*(5), 2686–2696. https://doi.org/10.1016/j.eneco.2008.03.003

Prabheesh, K. P., Padhan, R., & Garg, B. (2020). COVID-19 and the oil price–stock market nexus: Evidence from net oil-importing countries. *Energy Research Letters*, *1*(2), 13745. https://doi.org/10.46557/001c.13745

Salisu, A. A., & Adediran, I. A. (2020). Uncertainty due to infectious diseases and energy market volatility. *Energy Research Letters*, *1*(2), 14185. https://doi.org/10.46557/001c.14185

Salisu, A. A., Cuñado, J., Isah, K., & Gupta, R. (2020). Oil Price and Exchange Rate Behaviour of the BRICS. *Emerging Markets Finance and Trade*. In press. https://doi.org/10.1080/1540496x.2020.1850440

Salisu, A. A., & Mobolaji, H. (2013). Modeling returns and volatility transmission between oil price and US–Nigeria exchange rate. *Energy Economics*, *39*, 169–176. https://doi.org/10.1016/j.eneco.2013.05.003

Salisu, A. A., Raheem, I. D., & Eigbiremolen, G. O. (2020). The behaviour of US stocks to financial and health risks. *International Journal of Finance & Economics*. https://doi.org/10.1002/ijfe.2390

Salisu, A. A., & Sikiru, A. A. (2020). Pandemics and the Asia-Pacific Islamic stocks. *Asian Economics Letters*, *1*(1), 17413. https://doi.org/10.46557/001c.17413

Sharma, S. S., Phan, D. H. B., & Iyke, B. (2019). Do oil prices predict Indonesian macroeconomy? *Economic Modelling*, *82*, 2–12. https://doi.org/10.1016/j.econmod.2019.08.008

Westerlund, J., & Narayan, P. K. (2012). Does the choice of estimator matter when forecasting returns? *Journal of Banking & Finance*, *36*(9), 2632–2640. https://doi.org/10.1016/j.jbankfin.2012.06.005

Westerlund, J., & Narayan, P. K. (2015). Testing for Predictability in Conditionally Heteroskedastic Stock Returns. *Journal of Financial Econometrics*, *13*(2), 342–375. https://doi.org/10.1093/jjfinec/nbu001