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EXCHANGE RATE VOLATILITY SPILLOVERS TO GOLD PRICES IN SRI LANKA: EVIDENCE FROM A HYBRID ECONOMETRIC–MACHINE LEARNING FRAMEWORK

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Abstract

This study examines spillovers of means and volatilities between the exchange rates and the gold price in Sri Lanka. Both linear and nonlinear spillover channels are explored under a hybrid econometric-machine learning framework. The data consists of daily spot price of local gold and USD/LKR exchange rate over the period 2018-2025. In terms of methodology, the empirical strategy includes Granger causality test, HAC regression of volatility, various GARCH models, Random Forest estimator, and time series cross-validation. It was found that exchange rates strongly influence gold prices and provide predictive signals for future movements. The volatility regression revealed a positive relationship between the exchange-rate volatility and the gold-market volatility. Nonetheless, the GARCH model showed that the relationship is not significant in dynamic and conditional settings, even after controlling for volatility persistence, suggesting little evidence of structural volatility transmission. Volatility persistence in the Sri Lankan gold market is quite high ($\alpha + \beta = 0.947$). Random Forest estimator has a very good fit, explaining 95.89% of variation in volatility of gold market. Lagged gold and exchange-rate volatility proved the most informative predictors in the regression. The forecasting model was validated using time-series cross-validation. This study emphasises the importance of distinguishing between structural spillover channel and predictability of financial markets in risk transmission process. The study provides original evidence based on combining econometric and machine learning methods in an emerging economy.

Keywords: Gold Prices; Exchange Rate; Volatility Spillovers; GARCH; Random Forest; Sri Lanka.

1. Introduction

Gold is known to be used as a store of wealth and as an insurance against risk, especially in macroeconomically unstable economies with depreciating exchange rates. In emerging economies, changes in exchange rates can significantly affect asset values, the decisions made by the investors, as well as financial stability. Currency depreciation leads to gold's appreciation in domestic currency and may increase hedging requirements, thereby increasing gold prices' volatility (Toraman et al., 2011; Wang, 2013). Furthermore, the use of gold as a haven during periods of high economic and political instability strengthens the link between the exchange rate and the gold price (Qin et al.,

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2020; Apergis et al., 2021). The main theories explaining the connection between exchange rate and gold price include the asset-market theory and safe-haven theory. According to the former theory, exchange rate is viewed as an indication of the relative attractiveness of international financial assets, and therefore, the impact of the change in currency's exchange rate on the asset price is direct (Dooley et al., 1995; Wang & Lee, 2010). The latter theory suggests that demand for gold increases during economic and financial uncertainty, especially when there is risk to the domestic currency (Baur & Lucey, 2010; Guris & Kiran, 2014). Even though the connection between exchange rates and gold prices is theoretically and empirically justified, it is not entirely clear what kind of connection this is. It is hard to assess whether the co-movement is caused by economic spillovers arising from market behaviour and risk transmission, or simply a mechanical effect associated with currency conversion. Since gold price in the international market is normally denominated in US dollars, any changes in the exchange rate of the country automatically cause changes in gold price even if the gold price does not change in the international market. In other words, differentiating between predictive relationships, volatility co-movements, and volatility transmission presents an enormous empirical challenge in emerging economies with unstable exchange rates.

There is extensive literature about linkage between exchange rate and gold price based on econometric analyses of time series using Vector Autoregressive model, Granger causality test, GARCH family of models, and other techniques (Toraman et al., 2011; Qin et al., 2020). According to the findings, there are bidirectional relationships and volatility transmission between the exchange rate and the gold markets. However, the magnitudes and directions of these relationships vary across cases. Finally, it has been proven that these relationships are often non-linear, lagged, regime-dependent, and others. Recently, Random Forests and neural network machine learning algorithms have been used to predict gold prices. Although these algorithms can help improve predictions, they are rarely used in tandem with econometric models, thereby allowing for economic interpretation of relationships. Although global evidence on exchange-rate and gold-market interactions continues to expand, the studies from the small emerging economies remain limited. Prior work done in Sri Lanka has focused heavily on studying exchange rates, their behaviors, volatilities, and factors affecting them through econometric methods (Rajakaruna, 2017; Dissanayaka et al., 2023). However, empirical studies that directly quantify exchange rate spillover effects on the local gold market using high-frequency daily data are scarce, especially during periods of macroeconomic instability. The current study focuses on the Sri Lankan economy, which

faced a significant economic crisis in 2022, marked by the sharp depreciation of the local currency, increased macroeconomic instability and volatility, and investor interest in buying gold as a safe-haven asset. Specific research gaps can be identified as follows. First, there is little evidence on how exchange rates impact the domestic gold market in Sri Lanka. Studies conducted by Rajakaruna (2017) and Dissanayaka et al. (2023), which examined determinants of exchange rates and their volatilities in Sri Lanka, used low-frequency monthly or quarterly data. While they could determine the effect on exchange rates, none of them studied how these effects spill into other markets; therefore, whether exchange rate shocks spill into the domestic gold market at the daily frequency remains unclear. Second, prior work either utilized traditional econometric approaches or relied on machine learning tools exclusively. This means that while forecasting capabilities of machine learning models have been demonstrated by Nguyen et al. (2021) and Tuncsiper (2023), the authors have not considered structural effects of volatility shocks on asset returns and did not explore determine whether predictive power corresponds to structural effects of volatility. Third, while the literature shows that an association exists between exchange rates and financial assets, there is little focus on distinguishing between predictive effects, volatility correlations, and structural spillover effects. This is relevant for understanding how exchange rate volatility structurally influences volatility in the local gold market, rather than merely being associated with gold price fluctuations.

The current study seeks to address the research gaps regarding the interaction between exchange rates and gold prices in Sri Lanka, using econometric and machine learning methods. It seeks to explore whether there is any predictive power in exchange rate returns relative to gold returns, investigate the transmission of volatility from exchange rates to gold prices, and test the significance of the predictive power of exchange rate volatility using machine learning approaches. The research is driven by the following research questions: RQ1: Do exchange rate returns have any predictive power for gold returns in Sri Lanka? RQ2: Is exchange rate volatility a significant source of volatility in gold prices, considering volatility persistence and the global gold price market situation? RQ3: Do exchange rate effects on gold prices show nonlinearity and lagged effects?

2. Literature Review and Model Development

2.1 Exchange Rate- Gold Price Linkages: Mean Spillovers

The relationship between exchange rates and gold prices has been thoroughly studied in international finance and asset pricing. In the asset market approach, exchange rates are used to

show how attractive financial assets are in different countries, meaning that changes in currency can affect the commodities traded internationally, such as gold (Dooley et al., 1995; Wang, 2013). When the local currency is devalued relative to the domestic currency, the cost of gold rises, which could drive investor demand and return behaviour. In practice, studies use vector autoregression (VAR) and Granger causality models to test predictive relationships between exchange rate returns and gold returns. Findings in both established and emerging markets indicate that exchange rate fluctuations may carry predictive value for gold prices, but the level and direction of causality tend to vary over time and across market environments (Toraman et al., 2011; Wang & Lee, 2010). In some contexts, predictive effects are lagged rather than contemporaneous, which aligns with market friction and slow information diffusion. Empirical studies on the effects of exchange rates in the Sri Lankan context have mostly focused on exchange rate determinants rather than spillovers to commodity markets (Rajakaruna, 2017; Dissanayaka et al., 2023). Despite extensive international evidence, limited research has examined whether exchange-rate returns contain predictive information for gold returns in Sri Lanka using high-frequency data. Existing studies suggest that exchange-rate movements may influence commodity prices through valuation effects, investor expectations, and portfolio rebalancing mechanisms. However, the magnitude and persistence of these effects remain uncertain in emerging market settings. Based on the asset-market theory and prior empirical evidence on predictive spillovers between exchange-rate and commodity markets, the following hypothesis is proposed:

H_1: Exchange rate returns Granger-cause gold returns in Sri Lanka.

Both series are transformed into logarithmic returns:

$$r_t = \ln(P_t) - \ln(P_{t-1})$$

Where, usd_ret_t= log return of USD/LKR and $gold_ret_t$= log return of domestic gold price. To evaluate the Granger causality, the autoregressive model is estimated below.

$$gold_ret_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, gold_ret_{t-i} + \sum_{i=1}^{p} \beta_i \, usd_ret_{t-i} + \varepsilon_t$$

Exchange rate returns Granger-cause gold returns if:

$$H_0: \beta_1 = \beta_2 = \ldots = \beta_p = 0$$

is rejected.

2.2 Spillover Mechanisms of Volatility.

Beyond the mean dynamics, volatility transmission is a major channel through which shocks can be transferred across markets. With exchange rates and gold, currency volatility may amplify gold price volatility. Volatility regressions and GARCH-family models are often used to measure such transmission in empirical research, and it has been shown that exchange rate volatility is linked to gold volatility, especially during the crisis period and in periods of increased macroeconomic uncertainty (Qin et al., 2020; Apergis et al., 2021). The role of gold as a safe-haven can also reinforce this connection in the event of a rise in currency risk (Baur & Lucey, 2010; Guris & Kiran, 2014). The practical issue with volatility regressions is that measures of volatility are typically highly persistent, which may cause serial correlation and dynamic misspecification in a static regression. Thus, volatility transmission will be evaluated using reduced-form regressions and specifications that account for volatility persistence.

Therefore, the second hypothesis is as follows:

H_2: Exchange-rate volatility positively influences gold-price volatility after controlling for volatility persistence.

Volatility is constructed using a rolling 20-day standard deviation: The 20-day window is chosen to approximate one calendar month of trading activity, consistent with the convention adopted in prior volatility studies in emerging markets (Toraman et al., 2011; Qin et al., 2020). To assess the robustness of this specification, sensitivity analyses were conducted using 10-day and 30-day windows. Based on the HAC estimation, the specific rolling choice is performed.

$$\sigma_t = \sqrt{\frac{1}{n-1}\sum_{i=0}^{n-1}(r_{t-i} - \bar{r})^2}$$

where $n = 20$, usd_vol_t= rolling exchange rate volatility and $gold_vol_t$= rolling gold return volatility.

The Linear Regression Model is:

$$gold_vol_t = \gamma_0 + \gamma_1 usd_vol_t + u_t$$

Serial Correlation is corrected using Newey-West HAC standard errors. The following dynamic model estimates the volatility's persistence.

$$gold_vol_t = \delta_0 + \rho gold_vol_{t-1} + \delta_1 usd_vol_t + v_t$$

Because:

$$Gold_{LKR,t} = Gold_{USD,t} \times (USD/LKR)_t$$

Observed volatility co-movement may partially reflect arithmetic pass-through. International gold volatility is included in the model to reduce the arithmetic pass-through.

$$gold_vol_t = \theta_0 + \theta_1 usd_vol_t + \theta_2 int_gold_vol_t + e_t$$

If $\theta_1$remains statistically significant, the exchange rate effect could not be attributed solely to mechanical valuation. GARCH and GARCH-X models are estimated to investigate conditional volatility persistence and transmission mechanisms;

Baseline GARCH(1,1):

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}$$

Extended GARCH-X:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma usd_vol_{t-1}$$

Where, h_t= conditional variance and γcaptures structural volatility spillover. log-likelihood and information criteria are used for the model comparison. Given evidence of non-normality in financial returns, models are estimated under both Gaussian and Student-t distributions to ensure robustness.

2.3 Nonlinear and Hybrid Modelling Views

Since linear econometric models are structured inference, there is increasing evidence indicating that the exchange rate-gold relation can display nonlinear, interaction and regime-based behaviour. The spillovers can be asymmetric and lag-dependent, and cannot be well modelled by linear

specifications, as threshold effects and crisis dynamics drive them (Güriş & Kiran, 2014; Qin et al., 2020).

The most recent developments use machine learning approaches, such as Random Forests, to incorporate nonlinear dependence, more interactions, and intricate lag structures, without making strong assumptions (Nguyen et al., 2021; Tuncsiper, 2023; Xiong & Zhang, 2024). Though these techniques are often used to enhance the predictive performance, they are not usually directly integrated into econometric inferences, as this constrains interpretation. A hybrid strategy allows triangulation: the triangulation of the form of inference and the form of structure is offered by econometric approaches, whereas the triangulation of the form of flexible prediction and the form of interaction detection is offered by machine learning.mTherefore, the third hypothesis is the following:

H3: Exchange-rate variables, particularly exchange-rate volatility, are significant predictors of gold-price volatility within a nonlinear modelling framework.

Random Forest regression is estimated:

$$gold_vol_t = f(usd_vol_t, usd_ret_{t-1\ldots p}, gold_ret_{t-1\ldots p}) + \epsilon_t$$

The model is trained using time-series cross-validation. Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are used for evaluating predictive performance.

2.4 Combines Empirical Framework.

The empirical approach is a combination of three complementary approaches. In the analysis, Granger causality tests examine mean spillovers in returns, volatility regressions and conditional variance modelling estimate volatility transmission across persistence, and the Random Forest model produces nonlinear relationships and interactional predictive patterns. Such a hybrid framework combines the interpretability of economic performance with the predictive flexibility to offer a comprehensive picture of exchange rate spillover dynamics in a small emerging economy.

3.0 Methodology

The data from 2nd January 2018 to 26th December 2025 were obtained from the Central Bank of Sri Lanka (CBSL) website. In the sample years included, the data were affected by the macroeconomic stress, the COVID-19 pandemic and the Sri Lankan financial crisis. Daily data are preferred because volatility clustering and short-run spillovers are more accurately detected at

higher frequencies (Toraman et al., 2011). After aligning trading calendars and removing missing observations, the final sample consists of 1,905 daily observations. R software was used to analyse the data. The Augmented Dickey-Fuller test (ADF) is used to test for stationarity of the data. Then the Granger causality test provides estimates of mean spillovers, dynamic volatility regressions are used to analyse volatility transmission, and GARCH and GARCH-X models are estimated to examine the structures of the conditional variance and the Random Forest model effectively captures nonlinear and interaction-based spillovers and tests predictive dominance using time-series cross-validation.

4.0 Data analysis

4.1 Time series evaluation

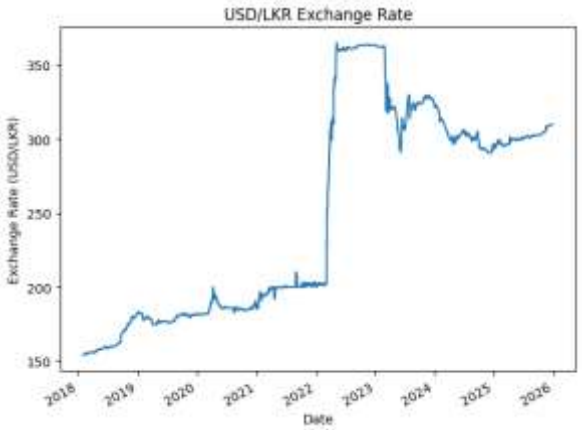


Figure 1: USD/LKR exchange rate.

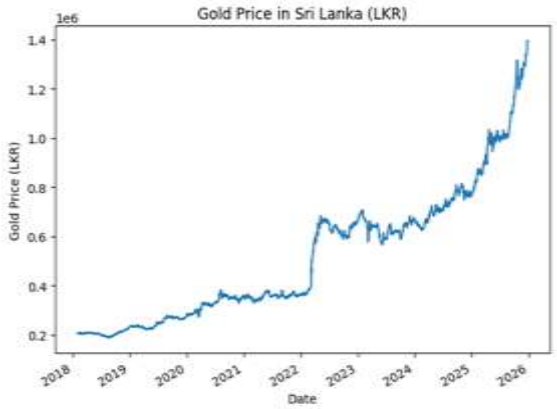


Figure 2: Gold price in Sri Lanka

Figures 1 and 2 show the evolution of gold prices and the USD/LKR exchange rate over the sample period. The two series show steep upward trends, especially during the exchange rate crisis. The USD/LKR exchange rate has experienced a series of sharp depreciations, while gold prices have shown robust gains during periods of currency stress. This graphical data is consistent with the theoretical assumption that gold prices are sensitive to exchange rate changes in an emerging economy.

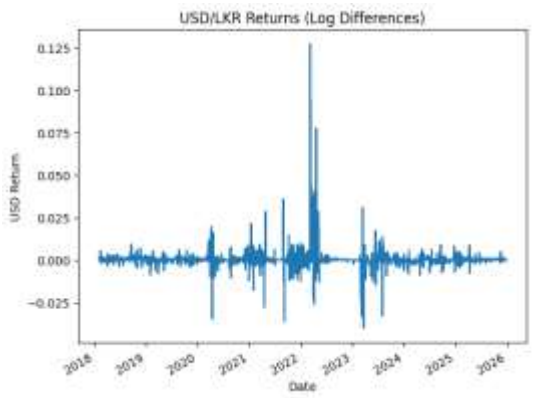


Figure 3 USD/LKR logarithmic series

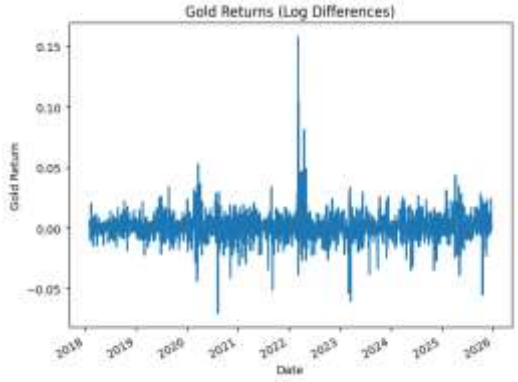


Figure 4 Gold price logarithmic series

The exchange rate returns and gold returns are the logarithmic series of returns, as shown in Figures 3 and 4. Both the returning series have near-zero means with definite volatility concentrations, especially during crises. Volatility bursts are indicative of changing risk regimes over time and warrant investigation of volatility spillovers.

4.2 Descriptive statistics

Table 01 descriptives

Variable	Count	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	Jarque–Bera	p-value
Gold Returns	1924	0.0010	0.0115	-0.070	0.1580	1.5779	28.0118	50,949.95	<0.001
Exchange Rate Returns	1924	0.0004	0.0062	-0.040	0.1272	7.7635	145.5208	1,647,686.17	<0.001

The descriptive statistics of gold return and exchange rate return are presented in Table 1. Both returns have rather low average daily returns (mean = 0.0010, mean = 0.0004), but gold returns are characterised by higher volatility, with a standard deviation of 0.0115 compared to 0.0062 for exchange rate returns. The wide range between the minimum and maximum indicates a rather large number of changes in the financial market. For gold returns, skewness is 1.578, and kurtosis is 28.012. In turn, for exchange rate returns, skewness is 7.764, and kurtosis is 145.521. These indicators imply that the distribution of exchange rate returns is far from normal, with an asymmetric shape and fat tails, which explains the high kurtosis and skewness. The null hypothesis of normality was rejected with respect to both returns by the Jarque-Bera test at $p < 0.001$. Thus, it is expected that the non-normality of returns will be reflected in further research using the Student-t distribution and the nonlinearity of returns.

4.3 Stationarity Tests

Table 2 Stationary test

Variable	ADF Statistic	p-value	Order of Integration
Gold Price (Gold_LKR)	0.979	0.990	I(1)
Exchange Rate (USD_LKR)	-1.620	0.739	I(1)
Gold Returns	-10.700	<0.01	I(0)
Exchange Rate Returns	-9.242	<0.01	I(0)

In Table 2, the Augmented Dickey-Fuller (ADF) test is employed to determine the stationarity characteristics of the price and return series. Results demonstrate that the level series of gold prices and the exchange rate are non-stationary, and the hypothesis of a unit root is accepted, as the p-values exceed 0.05. In other words, the time series shows evidence of stochasticity, and the considered variables are I(1). Conversely, the return series are stationary as the ADF statistics for gold returns (equal to -10.700) and the exchange-rate returns (equal to -9.242) are significant ($p < 0.01$) and imply rejecting the null hypothesis of a unit root. It means that the return series are stationary processes or I(0). The results obtained confirm the possibility of using the return series in further analyses.

4.4 VAR Order Selection

AIC(n)	HQ(n)	SC(n)	FPE(n)
10	2	2	10

Table 03 VAR Lag Order Selection Criteria

	AIC	HQ	SC	FPE
01	-1.945780e+01	-1.945121e+01	-1.943992e+01	3.544729e-09
02	-1.951343e+01	-1.950245e+01	-1.948363e+01	3.352931e-09
03	-1.951108e+01	-1.949570e+01	-1.946936e+01	3.360817e-09
04	-1.950794e+01	-1.948817e+01	-1.945430e+01	3.371400e-09
05	-1.952376e+01	-1.949959e+01	-1.945820e+01	3.318479e-09
06	-1.952484e+01	-1.949628e+01	-1.944735e+01	3.314907e-09
07	-1.952327e+01	-1.949032e+01	-1.943387e+01	3.320095e-09
08	-1.952545e+01	-1.948811e+01	-1.942413e+01	3.312862e-09
09	-1.953251e+01	-1.949077e+01	-1.941927e+01	3.289559e-09
10	-1.953658e+01	-1.949045e+01	-1.941142e+01	3.276204e-09

Table 3 presents the lag-order selection results for the VAR model based on the Akaike Information Criterion (AIC), Hannan–Quinn Criterion (HQ), Schwarz Criterion (SC/BIC), and Final Prediction Error (FPE). The results indicate that AIC and FPE favour a lag length of ten, whereas both HQ and SC select a lag length of two. Given the large sample size and the stronger penalty imposed by the Schwarz Criterion on model complexity, a lag length of two was adopted for the subsequent VAR

and Granger causality analyses. Therefore, following the SC and HQ criteria, the VAR model was estimated with two lags.

4.5 Granger Causality Results

Table 4: Granger Causality

	F-statistic	p-value
USD returns do not Granger-cause Gold returns	12.158	<0.001
Gold returns do not Granger-cause USD returns	3.667	0.026

Table 4 presents the findings from the Granger causality tests at an optimal lag of 2, following the SC/BIC criterion as indicated in Table 3. Exchange-rate returns Granger-cause gold returns ($F = 12.158$; $p < 0.001$). In other words, past movements in the USD/LKR exchange rate help predict gold returns, supporting H1 and the asset-market view of exchange rates. According to the asset-market view, exchange-rate movements may affect domestic gold prices through various channels, such as valuation and hedging. On the other hand, gold returns Granger cause exchange-rate returns ($F = 3.667$; $p = 0.026$). Although there is some statistically significant evidence of a predictive relationship between the two time series, the relationship between exchange-rate returns and gold returns appears far more evident. Therefore, it can be concluded that there are predictive linkages between the two markets in both directions, although exchange-rate movements are somewhat more effective at predicting gold returns.

4.6 Baseline volatility spillover regression with HAC standard errors

Table 5. Baseline Volatility Spillover Regression with HAC Standard Errors

Variable	Coefficient	HAC Std. Error	t-statistic	p-value
Constant	0.0073	0.0002	30.184	<0.001
Exchange Rate Volatility (usd_vol)	0.8410	0.0505	16.665	<0.001

Note: HAC (Newey–West) standard errors are used to correct for heteroskedasticity and serial correlation.

The regression equation estimated using the HAC variance is provided in Table 5. It shows that exchange-rate volatility has a statistically significant, positive correlation with the volatility of the gold market in Sri Lanka. Specifically, the coefficient of the exchange-rate volatility is estimated at 0.841 ($t = 16.665$, $p < 0.001$). This means that greater uncertainty in the currency market tends to be associated with higher gold-price risk. Economically, a one-standard-deviation increase in exchange-rate volatility (which was about 0.006 in the data sample) implies an increase in gold-market risk by approximately 0.005. In other words, the increase represents about 75% of the

average gold-market risk. Thus, the results emphasize that exchange-rate volatility matters for the gold-price risk from an economic perspective, especially in the case of high pressure on the currency in question (e.g., during the 2022 Sri Lankan currency crisis). However, economically, it can be concluded that higher exchange-rate volatility implies greater gold-price risk in Sri Lanka. Using HAC standard errors is essential to address potential heteroskedasticity and/or serial correlation in the data. Nevertheless, it must be emphasised that the above model represents a reduced form of the relationship and does not control for volatility persistence.

Table 6. Dynamic Volatility Regression

Variable	Coefficient	HAC Std. Error	t-statistic	p-value
Constant	0.0004	0.0002	2.378	0.017
Lagged Gold Volatility (gold_vol$_{t-1}$)	0.9428	0.0269	35.103	<0.001
Exchange Rate Volatility (usd_vol)	0.0542	0.0386	1.405	0.160

Table 6 presents a dynamic volatility regression that was estimated by including lagged gold-market volatility as an additional explanatory variable. The results indicate that lagged gold volatility has a strong, statistically significant effect on current gold volatility ($\beta = 0.943$, $p < 0.001$), confirming the high volatility persistence in the Sri Lankan gold market. In contrast, the coefficient associated with exchange-rate volatility becomes statistically insignificant ($\beta = 0.054$, $p = 0.160$) after accounting for persistence. This finding suggests that the significant relationship observed in the baseline HAC regression may largely reflect the influence of volatility persistence rather than an independent structural effect of exchange-rate volatility. The results therefore indicate that past gold-market volatility is the dominant determinant of current volatility, while the direct contribution of exchange-rate volatility becomes substantially weaker after controlling persistence. This finding highlights the importance of modelling volatility dynamics explicitly when assessing spillover effects between financial markets.

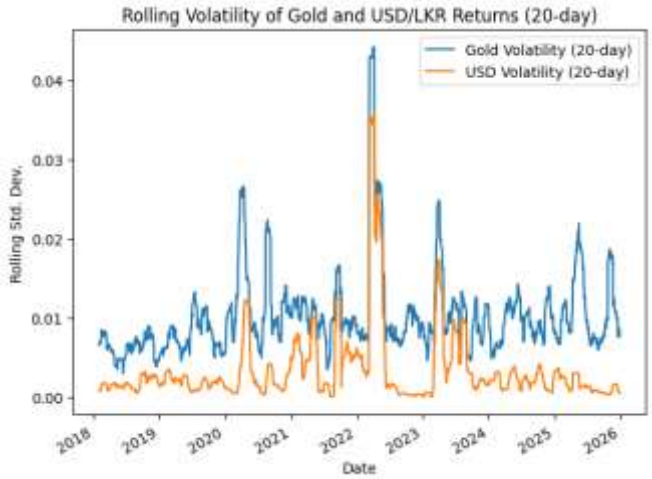


Figure 5: Rolling volatility of the gold returns and USD/LKR exchange rate returns in a 20-day period

Figure 5 illustrates the 20-day rolling volatility of gold returns and USD/LKR exchange-rate returns over the sample period. First, both series exhibit pronounced volatility clustering, a well-documented characteristic of financial time-series data. Periods of relative stability are interspersed with episodes of heightened volatility, indicating that volatility tends to persist over time rather than occurring randomly. Second, substantial volatility spikes are observed during the 2022 Sri Lankan currency crisis. Exchange-rate volatility increased sharply during this period, accompanied by elevated volatility in the gold market. The simultaneous occurrence of volatility peaks in both markets suggests that they were exposed to common macroeconomic shocks and heightened financial uncertainty. Third, the figure reveals periods of noticeable co-movement between exchange-rate volatility and gold-market volatility. Episodes of extreme currency-market turbulence are often associated with increases in gold-market volatility. While this visual evidence supports the existence of a positive association between the two markets, it does not by itself establish a structural volatility transmission mechanism. Therefore, formal econometric analyses are required to determine whether the observed relationship remains significant after controlling for volatility persistence and other dynamic effects.

4.7 Volatility Spillover Robustness: GARCH Framework

Table 7. Student-t GARCH(1,1) Results

Parameter	Estimate	Robust Std. Error	t-value	p-value
μ	0.000812	0.000192	4.232	<0.001
ω	0.000007	0.000001	7.041	<0.001
α_1 (ARCH)	0.0918	0.0088	10.465	<0.001
β_1 (GARCH)	0.8549	0.0149	57.186	<0.001
Shape (ν)	4.1915	0.4269	9.819	<0.001

Table 7 presents the findings from a student-t-symmetric GARCH(1,1) model estimated. The results indicate that both the ARCH coefficient ($\alpha = 0.092$, $p < 0.001$) and the GARCH coefficient ($\beta = 0.855$, $p < 0.001$) are statistically positive significant, confirming substantial volatility persistence in the Sri Lankan gold market. The persistence measure ($\alpha + \beta = 0.947$) is close to unity, indicating that volatility shocks dissipate gradually over time. The results suggest that current volatility is heavily influenced by past volatility, highlighting the importance of persistence effects in explaining

gold-market volatility. The estimated Student-t shape parameter ($\nu = 4.191$, $p < 0.001$) indicates the presence of fat-tailed return distributions, implying that extreme price movements occur more frequently than would be expected under a normal distribution. This is also justified by the descriptive statistics, which revealed substantial excess kurtosis in both gold and exchange-rate returns.

4.8 Conditional Volatility Model

Table 8. Conditional Volatility Model

Variable	Coefficient	HAC Std. Error	t-statistic	p-value
Constant	0.0004	0.0002	2.378	0.017
Lagged Gold Volatility ($gold_vol_{t-1}$)	0.9428	0.0269	35.103	<0.001
Exchange Rate Volatility (usd_vol)	0.0542	0.0386	1.405	0.160

Table 8 presents the results of a conditional volatility model. The results reveal that lagged gold volatility exerts a strong, highly significant effect on current gold volatility ($\beta = 0.943$, $p < 0.001$), confirming the persistence of volatility in the Sri Lankan gold market. Even though exchange-rate volatility becomes statistically insignificant after controlling volatility persistence ($\beta = 0.054$, $p = 0.160$). It suggests that the significant relationship observed in the baseline HAC regression largely reflects the persistence inherent in gold-market volatility rather than an independent structural effect of exchange-rate volatility. The coefficient of lagged gold volatility is close to unity, indicating that volatility shocks dissipate gradually over time. Consequently, past gold-market volatility appears to be the dominant determinant of current volatility, while the direct contribution of exchange-rate volatility becomes considerably weaker once persistence effects are taken into account. These findings highlight the importance of controlling volatility dynamics when evaluating spillover effects between financial markets and provide preliminary evidence that volatility persistence may be more influential than contemporaneous exchange-rate volatility in explaining gold-market risk.

Table 9. Diagnostic Tests for the GARCH(1,1) Model

Test	Statistic	p-value
Ljung–Box (Residuals, Lag 5)	8.080	0.028
Ljung–Box (Squared Residuals, Lag 9)	5.275	0.390
ARCH-LM (Lag 7)	0.559	0.973
Nyblom Stability	33.263	–
Joint Sign Bias	1.509	0.680
Pearson GOF (50 groups)	60.150	0.132

Table 9 presents diagnostic tests for the estimation results, indicating inconclusive results regarding model adequacy. While weighted Ljung-Box statistics of the standardised residuals are statistically significant (p-value < 0.05), indicating the presence of residual autocorrelation and implying that some mean-dynamics dependencies have not been adequately modelled, weighted Ljung-Box statistics of the standardised squared residuals and the ARCH-LM statistics are statistically insignificant, which means that the model specification adequately accounts for volatility clustering and conditional heteroskedasticity. The Nyblom test for parameter stability indicates statistically significant deviations from model stability, as the joint statistics exceed the asymptotic critical value; however, this is expected given the major structural changes the country underwent during the 2022 currency crisis. The Sign Bias tests show no evidence of asymmetric volatility effects (they are statistically insignificant). Finally, the adjusted Pearson Goodness-of-Fit tests indicate that the Student-t distribution fits the data well. Even though the GARCH (1,1) model adequately captures conditional heteroskedasticity and volatility clustering in the Sri Lankan gold market, a statistically significant Ljung-Box statistic for the standardised residuals (p-value = 0.028) indicates that the basic model specification still fails to account for residual autocorrelation in the mean equation. An extension of the current specification using the ARMA-GARCH approach or a higher-order GARCH could be used in the future. Notwithstanding this model's inadequacy, the absence of statistically significant ARCH-LM statistics demonstrates that the model adequately captures the phenomenon under consideration. Additionally, the most important conclusions in the paper have been drawn from the analysis of the GARCH-X conditional variance equation.

4.9 Subsample estimates

Table 10. Subsample GARCH-X Volatility Spillover Estimates

Period	vxreg1 Estimate	Robust Std. Error	p-value	AIC
Pre-crisis	0.000000	0.002815	0.999996	-6.623
Crisis Period	0.000000	0.001116	0.999993	-6.078
Post-crisis	0.000000	0.000434	0.999991	-6.346

Table 10 explains that GARCH-X volatility varies across different economic regimes; the GARCH-X model was estimated separately for the pre-crisis, crisis, and post-crisis periods. The results consistently indicate that the exchange-rate volatility coefficient (vxreg1) remains statistically insignificant across all subsamples. The estimated coefficients are close to zero, with p-values exceeding 0.99. The results suggest that exchange-rate volatility does not exert a significant structural effect on conditional gold-market volatility, regardless of the prevailing economic environment. Although earlier reduced-form regressions revealed significant positive associations

between exchange-rate volatility and gold-market volatility, the GARCH-X results demonstrate that these relationships disappear once volatility persistence is explicitly incorporated into the conditional variance process. Through all subsamples, volatility persistence remains the dominant characteristic of gold-market volatility, as reflected by the consistently significant ARCH and GARCH parameters. The findings, therefore, indicate that exchange-rate volatility is associated with gold-market volatility at the reduced-form level but does not constitute an independent structural driver of conditional volatility. This result remains robust across pre-crisis, crisis, and post-crisis periods.

4.10 Machine Learning

Table 11. Machine Learning Robustness Comparison

Metric	Random Forest	GBM
MAE	0.000635	0.000461
RMSE	0.001009	0.000817
Variance Explained (%)	95.89	95.06

Table 12: Variable Importance Rankings

Rank	Random Forest (%IncMSE)	Value	GBM (Relative Influence %)	Value
1	gold_vol_l1	54.63	gold_vol_l1	85.72
2	usd_vol	25.40	usd_vol	13.88
3	usd_ret_l2	8.98	gold_ret_l2	0.20
4	usd_ret_l1	8.28	gold_ret_l5	0.06
5	gold_ret_l3	7.53	gold_ret_l1	0.05
6	gold_ret_l2	7.33	gold_ret_l3	0.03
7	gold_ret_l1	6.87	usd_ret_l1	0.03
8	gold_ret_l5	6.78	usd_ret_l2	0.02
9	—	—	gold_ret_l4	0.02

Source: Author's computation using R software.

The results reported in Tables 11 and 12 show the predictive performance and variables' importance statistics of the Random Forest (RF) and Gradient Boosting Machine (GBM) estimators. As shown in Table 11, the Random Forest estimator performs well in predicting the volatility of the Sri Lankan gold market, with an MAE of 0.000635, an RMSE of 0.001009, and an R^2 of 95.89%. To test robustness, another machine learning algorithm has been applied: the GBM model has been estimated using the same predictors as the RF model above. As a result, the following prediction statistics have been obtained: the MAE of 0.000461, RMSE of 0.000817, and R2 of 95.06%. Thus, the two models have similar forecasting accuracy. At the same time, the variable importance analysis shows that the lagged volatility of gold-market returns, named gold_vol_l1 in the estimation process, is the most important variable in both machine-learning algorithms. In the Random Forest model, gold_vol_l1 takes first place in terms of relative importance with %IncMSE equal to 54.63, while exchange rate volatility is in the second position with %IncMSE of 25.40. The

variable importance statistics for the GBM model indicate that lagged gold volatility is the most important, with a relative importance of 85.72%, while exchange rate volatility is second, with a relative importance of 13.88%. To evaluate the out-of-sample performance and robustness, a time-series cross-validation with a five-fold partition was used. In the out-of-sample estimation, the average values of MAE and RMSE for the Random Forest model are 0.000561 and 0.000899, respectively. Both statistics show relatively low standard deviation, implying stability in the forecasting power of the variables across different time samples. Results highlighted that the difference between econometric and machine learning methods lies in the fact that the GARCH-X model tests whether exchange rate volatility has a statistically significant impact on gold-market conditional volatility, controlling for its persistence. In contrast, Random Forest and GBM estimators focus on predicting conditional gold volatility without controlling for potential linear or non-linear interactions. Thus, exchange rate volatility might have valuable forecasting power despite the GARCH-X model failing to achieve statistical significance. Therefore, the machine learning results indicate that the volatility of the gold market in Sri Lanka is primarily determined by the inertia factor, while exchange rate volatility is a relevant predictor of the market's volatility.

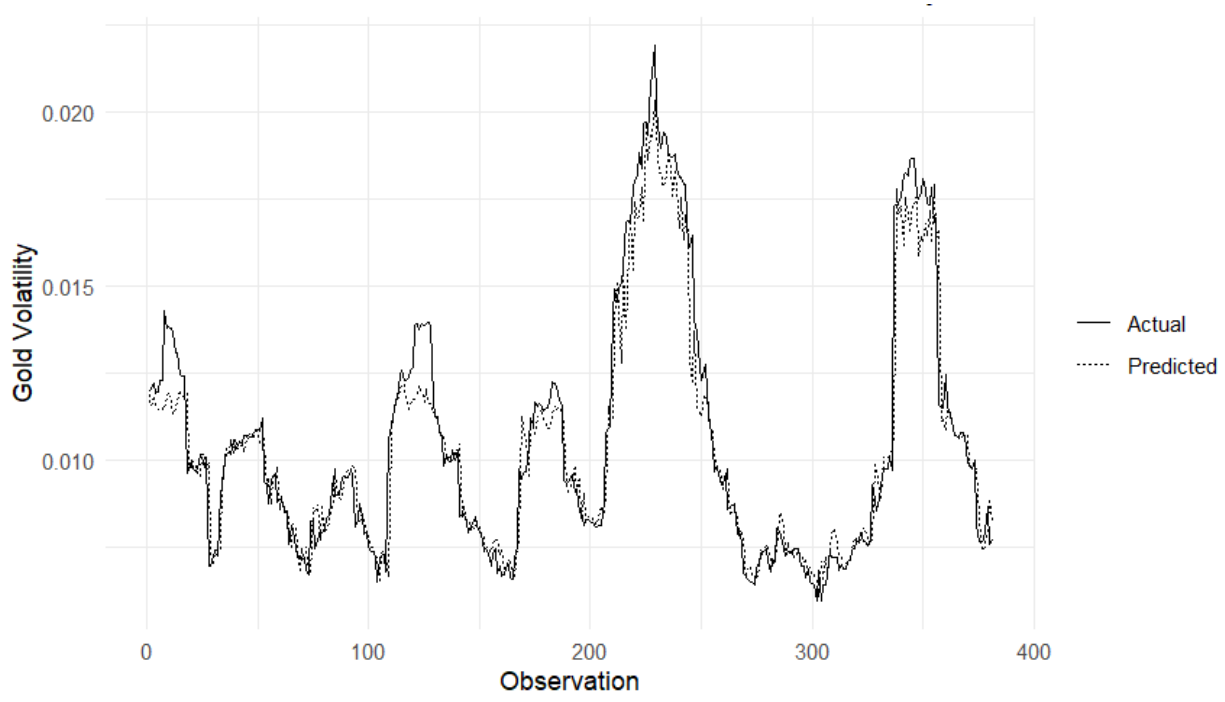


Figure 6: Random Forest Forecast: Actual vs Predicted.

Figure 6 presents the out-of-sample forecast performance of the Random Forest model. The predicted volatility closely tracks the actual gold-market volatility series throughout the period, capturing volatility clustering and major fluctuations. Although minor deviations are observed during periods of extreme volatility, the overall alignment between actual and predicted values demonstrates the model's strong forecasting capability.

4.11 Cross-Validation and Forecast Robustness

Table 13. Time-Series Cross-Validation Results

Fold	Test Sample	MAE	RMSE
1	1429–1523	0.000400	0.000566
2	1524–1618	0.000545	0.000835
3	1619–1713	0.000587	0.000917
4	1714–1808	0.000682	0.001039
5	1809–1903	0.000590	0.001140

Table 14.Cross-Validation Summary

Metric	Mean	Standard Deviation
MAE	0.000561	0.000103
RMSE	0.000899	0.000219

Tables 13 and 14: The stability and generalisation capability of the forecasting model were estimated using a five-fold time-series cross-validation procedure based on an expanding-window framework. The results indicate consistently low forecast errors across all validation folds. The MAE is 0.000561, while the RMSE is 0.000899. Furthermore, the standard deviations of the error measures are relatively small (MAE = 0.000103; RMSE = 0.000219), suggesting that predictive performance remains stable. Although forecasting errors vary slightly across individual folds, the overall consistency of the results indicates that the model generalises well over time and is not overly dependent on any specific sample period. These results support the robustness of the machine-learning forecasting framework and provide additional evidence that nonlinear relationships contribute to predicting gold-market volatility.

5. Discussion

The findings suggest that exchange-rate movements and gold prices are interconnected; however, the nature of this relationship differs between mean transmission, volatility dynamics, and predictive performance. The evidence indicates that the foreign-exchange market serves as an important source of information for the domestic gold market, consistent with the asset-market

perspective that internationally traded assets are influenced by currency fluctuations. Since gold is globally denominated in U.S. dollars, changes in the USD/LKR exchange rate directly affect the domestic valuation of gold. The stronger predictive influence of exchange-rate returns on gold returns, therefore, suggests that information is transmitted primarily from the currency market to the gold market rather than in the reverse direction. This finding implies that gold prices in Sri Lanka respond not only to developments in the global gold market but also to domestic currency conditions. The volatility analysis provides a more nuanced understanding of market interactions. While the reduced-form volatility regressions indicate a positive association between exchange-rate volatility and gold-market volatility, this relationship weakens once volatility persistence is explicitly incorporated into the modelling framework. This contrast suggests that the observed co-movement between the two markets should not automatically be interpreted as evidence of direct volatility transmission. Instead, both markets appear to respond to broader episodes of macroeconomic uncertainty, generating a common pattern of volatility. The results therefore imply that exchange-rate volatility functions primarily as an indicator of economic stress rather than as an independent structural driver of gold-market volatility. At the same time, the strong persistence observed in the conditional variance models indicates that gold-market risk is heavily influenced by its own historical volatility dynamics. Consequently, shocks to gold-market volatility tend to remain in the system for prolonged periods, reinforcing the importance of persistence in understanding risk behaviour in the Sri Lankan gold market.

The machine-learning results provide an important complementary perspective. The Random Forest and Gradient Boosting Machine models consistently identify lagged gold volatility and exchange-rate volatility as the most influential predictors of future gold-market volatility. This finding implies that currency-market uncertainty contains valuable forecasting information that may operate through nonlinear relationships, interaction effects, or threshold mechanisms, which are difficult to capture with conventional parametric models. Consequently, the apparent difference between the econometric and machine-learning results is not contradictory. Rather, it highlights the distinction between predictive relevance and structural significance. A variable may improve forecasting performance substantially without necessarily constituting a statistically significant determinant of conditional variance.

The study contributes to the literature by demonstrating that reduced-form volatility associations, structural volatility transmission, and predictive importance represent distinct dimensions of market

interconnectedness. While exchange-rate volatility is associated with gold-market volatility and improves forecasting performance, the evidence suggests that gold-market volatility remains predominantly persistence-driven. This distinction is particularly relevant in emerging financial markets, where nonlinear relationships and information frictions may limit the ability of conventional econometric models to capture the full complexity of risk transmission mechanisms.

6. Conclusion, Contributions, and Policy Implications

This study examines the spillovers in means and volatilities between the Sri Lankan exchange rate and the gold price. Daily observations are used to investigate mean and volatility spillovers using Granger causality, volatility regression, GARCH-family models, and machine-learning methods for forecasting. Exchange-rate returns exhibit strong predictability power for future gold returns. This implies that movements in the exchange rate are a major factor influencing the domestic gold price. Even though there is a positive association between the exchange rate and gold-market volatility in reduced-form specifications, this effect disappears after controlling for volatility persistence in gold markets. Therefore, there is limited evidence that foreign-exchange market volatility acts as an independent structural driver of gold-market volatility once volatility persistence is explicitly controlled for. Interestingly, the machine-learning results provide complementary evidence regarding the predictive role of exchange-rate volatility. Both the RF and GBM models identify lagged gold volatility and exchange-rate volatility as the two most important predictors of future gold-market volatility. These findings suggest that exchange-rate volatility contains valuable information for forecasting future gold-market risk, even though its structural influence on conditional gold-market volatility appears limited.This paper contributes to existing literature in three different ways. Firstly, it sheds new light on the interaction between the exchange rate and gold price series in Sri Lanka by employing high-frequency daily data. Secondly, it demonstrates the usefulness of distinguishing between volatility association and structural volatility spillover by combining volatility regression and GARCH models. Finally, it employs an integrated approach to show that exchange-rate volatility lacks predictive power, even though it may carry some predictive value. The practical implication of this study is that exchange-rate volatility could serve as a signal of future gold-market risk and therefore be considered in policymakers' and market participants' risk management decisions. Nevertheless, the study reveals the persistence of gold-market volatility, suggesting that risk-management activities must focus not only on exogenous factors but also on the volatility's persistence.

The paper's limitations arise from two major reasons. Firstly, the analysis does not consider the effects of additional macroeconomic variables such as interest rates, inflation, and other relevant macroeconomic indicators or shocks. Secondly, the considered time includes a very turbulent period related to the economic crisis in Sri Lanka. These facts are potential avenues for future research on volatility spillovers in emerging markets.

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