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Wavelet transformation and predictability of Gold Price Index Series with ARMA model

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Abstract: The U.S. gold futures market has recently attracted significant attention globally in the highly volatile equity and commodity futures markets. This study investigates an efficient algorithm based on ARMA denoising with wavelet transformation to measure the predictability of COMEX gold prices. The wavelet denoising decomposes and extracts the complex underlying structure and can reduce distortions occurring in the time series. The study has analyzed the COMEX gold time series for a period of the past five years, 2017-2022. The results show the outcome of alternative measures of predictability of the time series. The predictive measure with the traditional approaches assumes that the time series are linear and stationary over the long run and fails to explain the accuracy requirement in the short horizons. The results show a significant performance change compared to the conventional forecasting techniques.

Introduction

Globally, the upsurge in gold prices has a significant influence on the economy of a country through rising inflation, exchange rates and the stock markets, all of which lead to a slowdown in the country (Jacob and Kattookaran, 2019; Kumar and Patel, 2019; Sharifi et al., 2019; Ur Rahiman and Kodikal, 2019). Gold, as one of the most aggressively traded commodities, plays an important role as an industry input, and the price movements profoundly impact a country's overall economy. India is ranked number three in the list of gold importers across the globe. Therefore, any significant fluctuations enormously impact the exchange rate and the stock markets.

Recently, the gold sector has witnessed the most volatile phase due to COVID-19, due to a sudden decrease in the gold demand and the lack of adequate storage capacity (Hawaldar et al., 2020; Sharif et al., 2020). Dipping gold prices reduces inflation and promotes activity across the globe but burdens the fiscal balances and depreciation in the exchange rates in the countries that are net exporters of gold. At the same time, in countries like India which are the net importer of Gold, the fall in gold prices gravely hampers the foreign exchange reserves, inflation, and the demand for petroleum products (Iyke, 2020; Vidya and Prabheesh, 2020). It has been observed that while the effect of positive fluctuations takes time to materialize and benefit the gold importers, adverse changes display immediate reactions and sometimes highlight stress in the financial markets.

Given its role and impact on the country's economy, reliable and accurate forecasting models have been established to predict the movement of gold prices correctly. Instability in the price of Gold significantly influences the country's current account balance and foreign exchange reserves, the inflation rate in the economy, and the value of the domestic currency. Consequently, the gold crisis and the gold price movements have been anxiously growing among researchers and policymakers. In this context, the long-term trend analysis in gold prices has become more important for ensuring future economic stability in many countries. The techniques based on economic theory are mainly linear and parametric. These approaches are effective in understanding the price movements over the

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medium to long-term horizon with an improved computational efficiency.

Previous studies on gold price forecasting models have generally assumed that gold price trends persist and show similar future behaviour (Diaz et al., 2016; Jayaraman and Choong, 2009; Masih et al., 2011; Shahrestani and Rafei, 2020; Sujit and Kumar, 2011). Time series models like auto-regressive moving averages (ARMA) use historical information to identify patterns and have found better performance in predictive measures. There is no conclusive evidence from the previous studies that any predictive econometric model has consistently outperformed ARMA (Faisal, 2021; Nyangarika and Tang, 2018; Quan, 2014). A study (Quan, 2014) shows the performance of ARIMA models on gold price movements over a period from 2000-2010 (Nyangarika and Tang, 2018) conducted ARIMA model with exponential smoothing to estimate and forecast the gold and oil prices over the period 1991-2016. The results have shown an improvement in forecasting accuracy.

The results show that the ARIMA model yields the best performance. Faisal, 2021 carried out ARIMA models to examine the influence of gold on the economic growth of a country. The study has undertaken time series data from 1991 to 2019. Traditional forecasting models like ARIMA have been used to show the potential trends in global gold prices. The uncouth gold historical values prophesy the potential movement from gold prices, and the recommended model-based fallouts are compelling and honest.

Some recent development in predictive analytics includes nonlinear ensemble algorithms and wavelet denoising analysis. Wavelets conducts multi-scale analysis by decomposing the time series into the time scale domain (Gençay et al., 2005). The author finds very limited efforts in using wavelet analysis in gold price forecasting literature. Many previous studies have used the concept of wavelets to pre-process data before examining the time series (TS) and data mining (DM) techniques for prediction purposes. A study by Yousefi et al., 2005 used wavelet analysis to decompose Gold prices for prediction purposes (Gao et al., 2010; Yu et al., 2008). Traditional linear-based algorithms have achieved limited accuracy, while the recent nonlinear-based algorithms with artificial neural networks have outperformed with better accuracy (Xiong et al., 2013). An attempt by Murphy, 2002 to develop a wavelet decomposed ensemble model enhancing the forecasting ability with more understanding of the underlying structure of the time series.

The study uses the denoising technique to examine the wavelet signal processing in price movements of Gold. The wavelet denoising algorithms of wavelet families capture data characteristics of the time series to construct the forecasting ability. Thus, wavelet denoising can help analyzing the underlying key characteristics, hidden patterns of the time series data. The study's results confirm that the traditional approaches' forecasting ability improves with the separation of noises from the original data in the modeling process. The selection of the wavelets for denoising is based on the relative entropy that has resulted in better performance and improved robustness in the forecasting approach. The issue of selecting wavelets based on entropy for forecasting models has been less addressed in previous studies.

The present application of the wavelet denoising algorithm in predicting gold price movements has proved to have better stability in the estimates. The paper has been organized in the following manner. Section 2 presents the data used for analysis and the wavelet denoising algorithm. Section 3 discusses the major findings and performance evaluation results of the study, and finally, the conclusions and implications of the study are mentioned in Section 4.

Material and Methods

Data and Methodology

Gold has characteristics of both a commodity and money. It has been traded internationally between exchanges and banks as a spot or future, a commodity, and a financial asset due to its comparatively excellent value preservation and ease of storage. Commodity Exchange Inc. (COMEX), the oldest of the three markets examined in this study, was founded in 1933. In 1996, COMEX and the New York Mercantile Exchange (NYMEX) became the main futures and options markets for trading metals.

The study has collected data on daily trading prices of COMEX Gold from Yahoo Finance for the past five years May 2017 to April 2022. The data set during this time has witnessed the most volatile phase of history due to the novel coronavirus (COVID-19). The prices have been transformed to first-order level log differencing using $r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$. The transformation has been done to remove trend factors in the time series. The transformation has more attractive statistical properties like stationarity and corresponds to a percentage change in the transaction i.e., scale-free. This also attracts to fulfilling the assumptions in a time series like stationarity.

The time series has been analyzed on R using libraries: 'wavelets', 'wavethresh', 'fExtremes', 'waveslim', 'fNonlinear' and 'tseries'.

Wavelet Denoising Algorithm (WDA)

The WDA, in recent years, has received attention from researchers in the field of economics and finance. The approach is robust in removing the noises while preserving the underlying structure, such as the stationarity of the time series. The techniques use wavelet functions over both time and frequency scales during the data denoising. Wavelet analysis projects the time series into the multiscale domain using the wavelet transform represented as:

$$W_j(k) = \int f(x)\psi\left(\frac{x-j}{k}\right)dx$$

where $\psi\left(\frac{x-j}{k}\right)$ Referring to the wavelet families and j, k are the time and frequency scale localizations, respectively. The wavelet transform decomposes the data based on the characteristics across scales in the different domains, denoised and noises.

$$x_t = x_{denoised,t,w} + x_{noises,t,w}$$

The next step is followed by modeling the conditional mean of the denoised data using the autoregressive moving average (ARMA) process as represented in the following:

$$x_{denoised,t} = \delta_t + \sum_{i=1}^{p}\phi_j x_{t-i} + \sum_{j=1}^{q}\theta_j \varepsilon_{t-j} + \varepsilon_t$$

Where x_{t-i} denotes the returns at p lags with parameter ϕ_j (AR(P)), and ε_{t-j} denotes the residuals at q lags with parameter θ_j (MA(q)). The optimal specification of (p,q) is determined based on AIC and BIC criteria.

With a high dimensional set of forecasts 'G' is based on different wavelet parameters, and ICA with 'S' projected principal components are used to remove noises from the data and transformed using the following:

$$\mu_t^S = A^{-1}\mu_t^G$$

Where 'A' is the real coefficient?

Finally, the optimal weights are obtained from nonlinear ensemble processes using the least square support vector regression (LSSVR) algorithm. The WDN-ICA-LSSVR aggregates the individual conditional means in the ICA transformed forecast matrix represented as:

$$\mu_t = \phi_{i\epsilon S}(\mu_t^i)$$

Results

Figure 1 shows the price movement of gold from 2017 to 2022. Figure 2 presents the box-whisker plots presenting minimum, maximum, first quartile, second quartile and the third quartile. The box-whisker plots have been represented for quarterly data during the study period. The results show a significant variation during April-June 2020, when it touched an all-time high of \$2043.80. This quarter also shows a significant difference in the minimum and maximum values. The post-June 2021, the market rebounded and touched to previous levels of prices. The significant asymmetry reflects a deviation from the normal distribution and exhibits a nonlinearity in the data. Further, the study has examined the stationarity of gold prices. Figure 3 depicts the autocorrelation function (ACF) of the prices, showing a serial correlation in the higher lags. Therefore, the data has been transformed to logarithmic returns and the ACF plot of the returns shows the decline in the correlation after few lags. Thus, the study has considered the logarithmic returns for extracting noised and denoised data from the original data series.

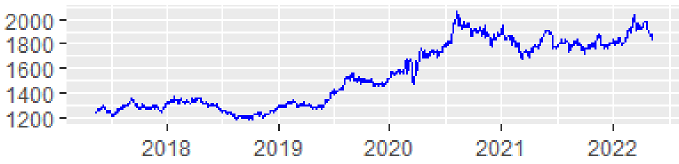


Figure 1. Line chart showing Gold Prices from May 2017-April 2022

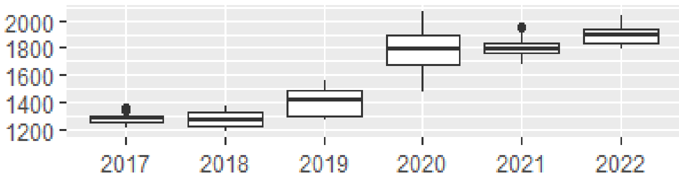


Figure 2. Box-whisker plot showing Five number summary of different quarters during 2017-2022

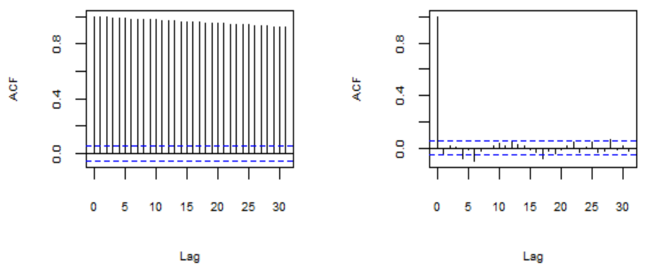


Figure 3. Auto-correlation Function (ACF) of the original data series and the logarithmic returns

Table 1 presents the descriptive statistics of extracted noises and denoised returns from the original data series. We examined the nonlinearity characteristics using Brock-Dechert-Scheinkman (BDS) test. Since p<0.001 in all the time series (noise and denoised), the results confirm that return series are not independently and identically distributed (IID) and contains nonlinear dynamics. The significance of the JB test confirms that the return series is abnormal. The results are consistent with the observations that persist with frequent shocks and large volatile events.

Results show that the optimal wavelets for the original data series, noises, and denoised data are DaubExPhase 1, DaubExPhase 3, and DaubLeAsymm 10, respectively. In

Table 1. Descriptive statistics

Statistics	x_t	$x_{noises,t,w}$	$x_{denoised,t,w}$
Mean	0.0003286	0.04842	0.000000
Quartile 1	-0.0037893	-0.18588	-0.002861
Median	0.0006203	0.08315	0.00000
Quartile 3	0.0053404	0.30347	0.002861
Minimum	-0.0511396	-0.50250	-0.009668
Maximum	0.0580527	0.49626	0.009668
JB test	1409.1***	36.038***	12.631**
BDS test	2.0294**	372.61***	32.37***
**p<0.01 ***p<0.001			

Table 2. Relative Entropy for selection of Wavelet

Sl.No.	Wavelet family	x_t	$x_{noises,t,w}$	$x_{denoised,t,w}$
1	DaubExPhase 1	**0.09856266**	6.738229	0.4834984
2	DaubExPhase 2	0.10949229	6.086014	0.358351
3	DaubExPhase 3	0.17807595	4.971020	0.4669421
4	DaubExPhase 4	0.24880804	4.252855	0.3219027
5	DaubExPhase 5	0.27176591	4.938632	0.386812
6	DaubExPhase 6	0.25682434	5.107216	0.4196595
7	DaubExPhase 7	0.22171431	4.855617	0.4437885
8	DaubExPhase 8	0.20400047	4.574101	0.3944167
9	DaubExPhase 9	0.18828955	4.314409	0.3603841
10	DaubExPhase 10	0.1906389	**4.069662**	0.4798205
11	DaubLeAsymm 10	0.18169442	5.144417	**0.2851688**
12	LinaMayrand 5.4	0.21153037	4.891531	0.498643

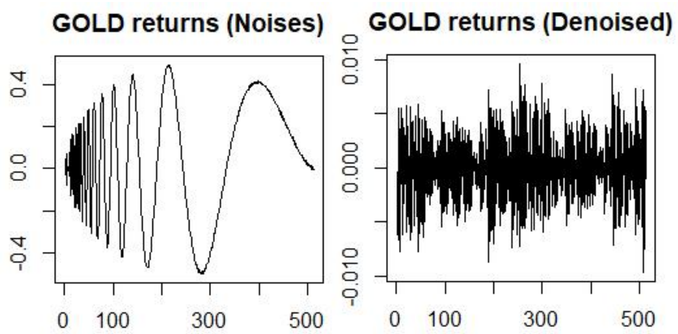
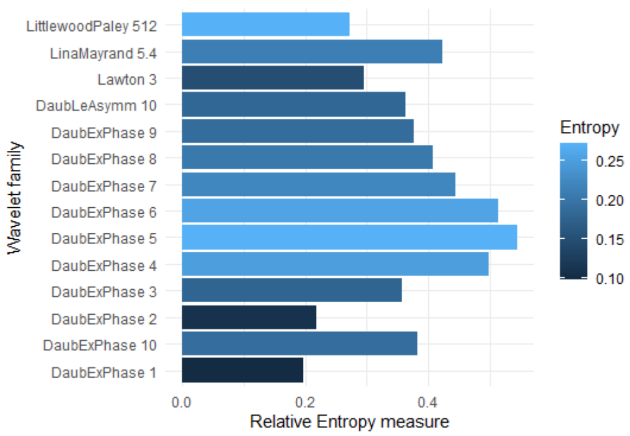


Figure 4. Gold returns (Noises) and Gold returns (Denoised)

The study has considered the Shanon entropy-based function for selecting optimal wavelet among Daubechies (vanishing moments 1 through 10) (see table 2) for the original return series data, denoised and the noised separately. Shanon entropy is calculated on the squared values of wavelet coefficients. The results are also presented in the bar plot (Figure 5).

sample forecasting, the accuracy of the time series has been measured with root mean square errors (RMSE) and mean absolute deviations (MAD). Among the forecasting techniques, ARMA model has outperformed and has minimum forecasting errors for original and denoised time series. Auto-regressive performance was better in noise data in comparison to other forecasting models.



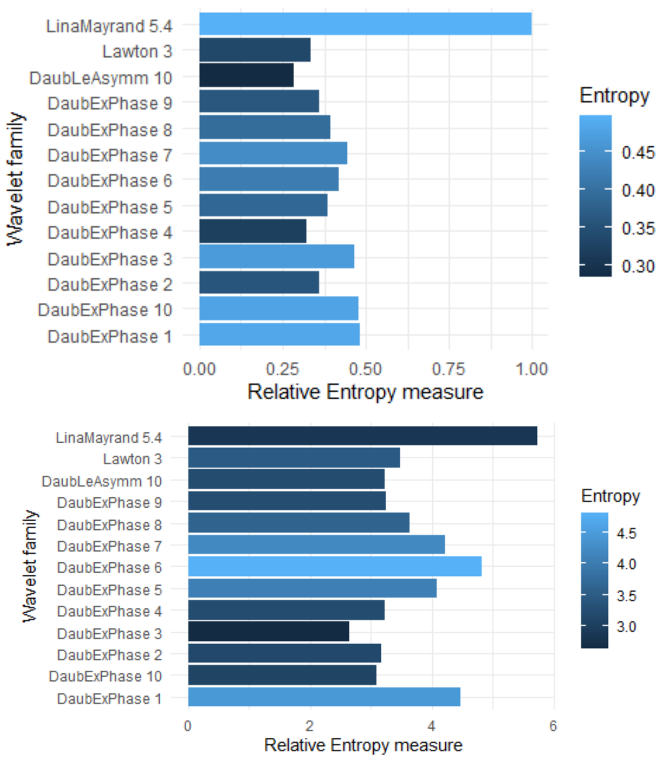


Figure 5. Relative entropy for selection of wavelet gold returns, noises, and denoised

Table 3. Wavelet denoising forecast accuracy of MA, AR, and ARMA models

	x_t		$x_{noises,t,w}$		$x_{denoised,t,w}$	
	DaubExPhase1 "HAAR"		**DaubExPhase 3 (D3)**		**DaubLeAsymm 10 (D10)**	
	RMSE	MAD	RMSE	MAD	RMSE	MAD
Moving Averages (MA(2))	0.564	0.397	0.624	0.537	0.286	0.224
Auto regressive (AR(1))	0.182	0.109	**0.143**	**0.125**	0.092	0.078
Auto regressive moving averages (ARMA (2,1))	**0.142**	**0.093**	0.171	0.154	**0.085**	**0.056**

Conclusions

Gold possesses both the qualities of a commodity and money. It is a well-liked hedging instrument during the era of risk aversion because of its high liquidity and low risk. The gold price trends have nonlinear dynamics and are influenced by noise brought on by extreme outliers. Thus, the separation of noises from the original data series was conducted to understand the underlying structure and the hidden patterns. The study has compared various forecasting models viz., moving averages, auto-regressive, and auto-regressive moving averages to predict gold prices with wavelet denoising. The appropriate selection of wavelet denoising techniques leads to better learning of the data and reaching a higher level of model generalizability. The findings show that DB1, DB3, and D10 were better in comparison to others in the wavelet family. The result findings show that the behavior of the denoised data is sensitive to the choice of the wavelet and can lead to better accuracy of forecasting models. This study has concluded that forecasting models like ARMA with wavelet denoising can offer better performance and improved robustness after separating the noises from the original data series.

Market participants need to carefully decide on investment plans based on the right predictable measures and look at the global economic condition, with specific attention to the price movement of gold. Historical data show an upward movement in gold prices in recent years. After a surge in prices during 2016-17, prices declined around 0.01% in 2018 due to increasing challenges in the international political economy. In 2019, gold prices saw an upward movement, increasing around 18.14%. The US dollar and changes in monetary policy have been the leading factors to influence the prices of gold and have always attracted significant attention in the market. Numerous countries have suffered economic harm as a result of the recent worldwide pandemic brought on by COVID-19, since the sequence of lockdowns had a detrimental effect on the world economy. Global investors made significant investments in gold, which led to a sharp surge. Investors must first define their risk appetite and expectations, undertake a logical study of the market environment, and pinpoint the key variables that will affect the price of gold throughout the forecast period. Investors might contemplate a fair increase in their gold holdings in their portfolios during a volatile market environment in order to diversify their investment risks. The percentage of gold allocation will depend on the portfolio's risk tolerance.

This research suggests that wavelet decomposition (or wavelet transform) can help better understand the time series data into detailed components. The forecasting models like ARMA with wavelet transform can provide better opportunities for predictability measures.

Conflict of Interest

Nil

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