Journal of Management Science and Engineering 6 (2021) 135–145

Contents lists available at ScienceDirect

Journal of Management Science and Engineering

journal homepage: www.keaipublishing.com/en/journals/journal-of-management-science-and-engineering/

Structural analysis and forecast of gold price returns

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ARTICLE INFO

Article history:
Available online 6 March 2021

Keywords:
SVAR
STL-ETS
Neural network
Bayesian structural time series model
Gold price returns

ABSTRACT

Gold has multiple attributes and its price is affected by various factors in the market. This paper studies the dynamic relationship between the gold price returns and its affecting factors. Then we use the STL-ETS, neural network and Bayesian structural time series model to predict the gold price returns, and compare their performance with the benchmark models. The results show that the shocks of crude oil returns and VIX have the positive effect on gold price returns, the shocks of the US dollar index have the negative effect on gold price returns. And the fluctuation of gold price returns mainly depends on crude oil price returns shocks. STL-ETS model can accurately fit the fluctuation trend of the gold price returns and improve prediction accuracy.

1. Introduction

As a financial asset, gold is widely circulated in the market; as a reserve asset, it is still one of the main assets of international reserve assets. Gold has always been a trusted investment tool. The research data of World Gold Council show that since 2001, worldwide investment demand for gold has increased by about 15% each year (World Gold Council, 2019a). According to the latest gold retail market survey report in 2019, among the investment products that investors have ever bought, gold ranks third with 46%, next to savings account (78%) and life insurance (54%). Gold is increasingly becoming a mainstream investment tool in the global market (World Gold Council, 2019b). The total purchases of gold by central banks in 2018 were 651 tons, an increase of 74% year-on-year, which became the peak of central banks gold purchase since the collapse of the Bretton Woods system in the 1970s. In the first half of 2019, the global central bank purchased 374.1 tons of gold, a year-on-year growth of 57%. Central banks' demand for gold has been increasing. Gold plays a more important role in reserve assets.

With the marketization of gold price and the constant adjustment of international pattern, gold is facing a more complicated market environment, and its price has been in a state of violent fluctuations. In March 2018, trade disputes between China and the United States broke out. According to Section 301, the amount of taxed products related to China increased from \$50 billion to \$2000 billion. The market reacted fiercely, and global stock markets fell to different degrees. The United States, Britain, and France carried out joint military strikes against Syria, the United States withdrew from the Iranian nuclear deal, and the geopolitical situation in the Middle East was tense, the turbulent market environment has caused the

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https://doi.org/10.1016/j.jmse.2021.02.011
2096-2320/

prices of safe-haven assets to rise, and gold has performed well during the risk aversion period. At present, global economic growth slows down. The Federal Reserve cut interest rates three times in 2019 and the European Central Bank restarted quantitative easing, the global monetary policy tends to be loose. The decline in bond yields has reduced the opportunity cost of holding gold, and gold has become a more attractive hedging and diversified investment tool. The price of gold has rebounded since 2016. Until October 31, 2019, gold prices rose by 450.95 dollars per troy ounce, an increase of about 42.54%.

Beckmann and Czudaj (2013) show that gold can be used as a hedging tool or safe haven asset. In general, the increase of uncertainty and volatility of the stock market and the tense geopolitical situation will cause the investor risk aversion heat up. The "safe haven" characteristic of gold attracts investors to enter the gold market and diversify their investment by adding gold into their portfolio, thereby diversifying risks and obtaining long-term returns. Under different policy backgrounds and market environments, the dominant driving factors behind gold prices will also change. In this context, the analysis of the influencing factors of gold price trend and the forecast of the gold price returns can instruct investors to make rational investment decisions and reduce investment risks.

In this paper, we construct SVAR model to analyze the dynamic relationship between gold price returns and its affecting factors in Section 3. Then, in Section 4, from two perspectives, STL-ETS and neural network are used to analyze and predict the sample series of historical data of returns, BSTS model is used to analyze and predict the sample series of market fundamental data. In Section 5, we give some conclusions and recommendations.

2. Literature review

Gold price has been widely concerned by investors and researchers, and there are plenty of literatures on the analysis and prediction of gold price. Since gold prices are greatly affected by macroeconomic factors, most of the research on the gold market focuses on the impact of macroeconomic variables of gold prices. Macroeconomic driving factors mainly include inflation rates, oil prices, stock prices, US dollar, exchange rates, interest rates, and so on. Microeconomic driving factors mainly include gold's convenience yield and gold lease rate (Lucey and O'Connor, 2013).

Cunado et al. (2019) illustrated in long-time mean-reverting behavior exist in gold price, and the cycle of gold price is about seven years. Aye et al. (2016) discovered the non-linear relationship between gold price and inflation. In the long run, gold can be used as an inflation hedge. However, this relationship may be interrupted as the market develops and its structure changes. Tiwari and Sahadudheen (2015) used the GARCH and EGARCH models to study the relationship between oil prices and gold prices, and the results showed a highly positive correlation between gold and oil (0.87). Gil-Alana et al. (2017) found cointegrated relationship (0.46) between gold and oil based on time series methods. Mo et al. (2017) used the daily data of gold spot prices, US dollar index, and oil prices between 1990 - 2016 to study the long-term time-varying relationship between these markets, and construct the DCC-MGARCH model. The results show that relationship between gold and oil is weakly positive. The relationship between oil and dollar is always negative, while the gold-dollar relationship is constantly changing. Raza et al. (2016), Singhal et al. (2019), Dong et al. (2012), Gokmenoglu and Fazlollahi (2015) studied the relationship between gold, oil and stock price in different counties. Raza et al. (2016) constructed a nonlinear ARDL (NARDL) model to study the nonlinear effects of gold prices, oil prices and related volatilities on stock prices of the top ten emerging stock markets, and concluded that the price of gold has positive impact on stock prices in China, Brazil, South Africa, Russia, India, crude oil prices have negative relationship between stock markets, and fluctuations in gold and crude oil markets reduce stock prices in the long run. Singhal et al. (2019) found the international gold price is positively related to stock price in Mexico based on the daily data from 2006 to 2018. Dong et al. (2012) showed that there is a dynamic positive correlation between the oil spot market and oil futures market, stock market, which is negatively correlated with the gold market. They used DCC-MVGARCH model to study the dynamic correlation between different financial markets based on the data of oil, stock and gold market trading days from 2004 to 2010. Gokmenoglu and Fazlollahi (2015) proved long-run negative relationship between gold price and stock price (-0.74) in US through ARDL co-integration approach.

The forecast of gold price can be mainly divided into two categories: one is to focus only on the gold price or its returns, and construct a univariate model to analyze and predict from the technical aspect; the other is to construct a multivariate model, considering the interaction between the influencing factors. In terms of methods, more scholars choose to combine traditional econometric models with artificial intelligence models to improve prediction accuracy. Liu et al. (2018) compared the ARIMA and NAR(1) models of the Au9999 spot price and made a short-term prediction of the gold prices. The results show that the non-parametric autoregressive model (NAR(P)) fits better. He et al. (2017) constructed a multivariate EMD denoising model to identify noise factors and predict the trend of precious metal prices. Compared with random walk (RW) and ARMA models, MEMD denoising prediction model can improve prediction accuracy. Selected samples are daily data of gold, silver, palladium and platinum from 1993 to 2016. Kristjanpoller and Minutolo (2015) combined the GARCH model with an artificial neural network. Compared with the GARCH model alone, the ANN-GARCH model can significantly reduce the prediction error of gold price volatility. Input variables of neural networks include exchange rate fluctuations, stock market returns, and oil price fluctuations. Pierdzioch et al. (2016) used the Quantile-Boosting method to make out-of-sample predictions of gold returns under the asymmetric loss function. The application of this method in gold market shows that the composition of the best prediction model depends on investor types. Optimistic investors benefit more from the rise of gold price than pessimistic investors. Risse (2019) used discrete wavelet transform (DWT) to decompose the forecasting series and then use support vector regression (SVR) to forecast gold excess returns and DWT-SVR can significantly improve the prediction accuracy (0.93) compared with other models. Alameer et al. (2019) found exchange rates, inflation rates, oil, metals all have strong predictive power for gold price fluctuations based WOA–NN model.

In general, most of the existing literatures on the gold market focus on its influencing factors, or on the improvement of traditional models to further increase the prediction accuracy for the price, analysis and prediction only from the technical or fundamental aspect. This paper comprehensively considers the dynamic impact and extent of the influencing factors on gold price returns, and uses the non-Gaussian SVAR model to extract the information contained in the data to the maximum extent. Secondly, we predict the gold price returns from the technical and fundamental aspects, the ARIMA and ETS models, which are widely used and relatively robust in the previous literatures, are selected as the benchmark models. And then selects significant factors to construct the Bayesian structural time series model, analyzes and predicts the gold price returns from fundamental perspective. Multi-angle and all-around comparison, choose the most suitable forecasting model for gold price returns with higher accuracy.

3. Dynamic effect analysis of gold price influencing factors based on SVAR model

3.1. Model and identification method

Vector autoregressive (VAR) model was proposed by Sims in 1980. Since then, it has been widely used to study the dynamic relationship between economic variables and also for some relevant predictions (Fresoli et al., 2015). Each endogenous variable in the VAR model is a function of the lagging value of all endogenous variables in the system (Sims, 1980; Man et al., 2019), but its current correlation is hidden in its innovation vector, so that the economic meaning of the impulse response function cannot be accurately explained. The SVAR model is the structural form of the VAR model, and the instantaneous structural relationships between variables are included in the model. The model is traditionally identified by imposing certain constraints, and the dynamic relationship between structural shock and economic variable is studied using impulse response functions and forecast error variance decomposition.

With the deepening of global financial integration and the innovation of financial products, the depth and breadth of the gold market continue to expand, and the co-movements effect between markets has strengthened. Based on the research of current market conditions, the price of gold is mainly affected by macroeconomic variables. Select crude oil prices and US dollar index that are most commonly used in the literature and are also closely related to gold prices. Due to the frequent occurrence of market risk events, the stock market volatility has increased, and the impact on the gold prices has intensified. Therefore, this article adds the VIX index to study the relationship between the current gold prices and stock market volatility. This paper chooses to construct SVAR model to explore the relationship between gold, crude oil, US dollar index and Chicago Board Options Exchange Volatility Index (VIX). Due to the complexity of the linkage between various markets, high-frequency data on prices is critical to understanding market operations and making investment decisions. We select the daily data of each variable, and the data set is preprocessed to eliminate non-overlapping data due to holidays. The variables are from January 3, 2006 to March 7, 2019, with 3281 data each. Gold price data comes from the World Gold Council, select LBMA gold price (Dollars per troy ounce). WTI crude oil spot price (Dollars per Barrel) comes from EIA. US dollar index and VIX are from Wind. Daily returns of price series are calculated using logarithmic return method. Let the returns series $Rt = ln(p_t / p_{t-1})$, where p_t and p_{t-1} are the prices of day t and day t-1, respectively. The price returns of gold, crude oil are denoted as G_t, O_t, US dollar index and VIX volatility are denoted as U_t, V_t.

First, construct a VAR model. The VAR model requires the use of stationary time series, and difference non-stationary series to obtain a stationary series and then establish the model. The ADF test was used to test the stationarity of the data used. Table 1 shows that the null hypothesis was rejected at the 1% significance level, all original time series are stationary, then we build a VAR model directly.

The determination of the lag length is an important issue in constructing the VAR model. When the lag length is large, the dynamic characteristics of the VAR model can be more clearly reflected, but this will increase the number of required estimation parameters and reduce the degree of freedom of the model. The VARselect function in R is used to calculate and select the optimal lag length p of the VAR model, the results of criteria are reported in Table 2. The lag length selected based on the AIC and FPE criteria is 2, and then construct the VAR(2) model. The AR roots graph (Fig. 1) shows that the reciprocals of roots fall within the unit circle, and the model constructed is stable. Based on the constructed VAR(2) model, built the SVAR model.

Considering k variables, p-order SVAR model:

Table 1
ADF test for the stationarity of time series.

Series	ADF	p-value
G_t	−15.101	0.01
O_t	−13.897	0.01
U_t	−14.344	0.01
V_t	−17.803	0.01

Table 2
The results of lag length criteria of VAR model.

Lag	AIC	HQ	SC	FPE
1	−32.38918	−32.37586	−32.35198	8.581371e-15
2	−32.39185	−32.36787	−32.32488	8.558473e-15
3	−32.38723	−32.35259	−32.29049	8.598179e-15
4	−32.38776	−32.34246	−32.26126	8.593583e-15
5	−32.38660	−32.33064	−32.23033	8.603580e-15

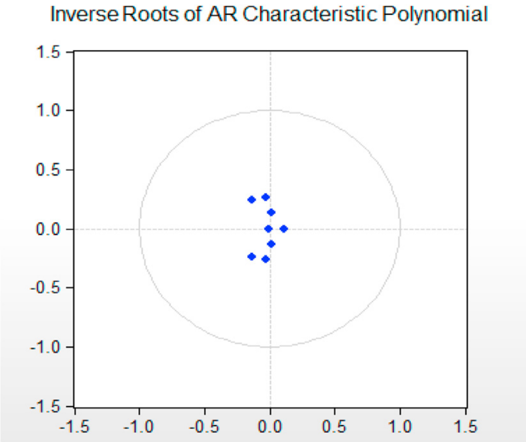

Fig. 1. AR Roots Graph of VAR model.

$$y_t = c_t + A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t = c_t + A_1 y_{t-1} + \ldots + A_p y_{t-p} + B\varepsilon_t \tag{1}$$

where y_t is an n-dimensional endogenous variable, c_t is an intercept term, and ε_t is a structural shock vector, assuming a zero mean and a positive definite covariance matrix. The reduced form u_t, is linear combination of the error term ε_t , and is composite shock.

The key to the SVAR model lies in the identification of its parameter matrix B. The traditional method is to impose long-term or short-term constraints on the parameters based on economic theory. Newer methods include the identification based on heteroscedasticity or the application of sign constraints (Su et al., 2016).

In this paper, the non-Gaussian SVAR identification method proposed by Lanne et al. (2017) is used to realize the identification. During the identification process, for the $B\varepsilon_t$ in (1), there exists an $n \times n$ non-singular matrix C, so that $B = BC, \varepsilon_t = C^{-1}\varepsilon_t$, which results in the estimated parameters are not unique and affects the explanation of impulse response functions. Limit the covariance matrix of the error term ε_t to a diagonal matrix such that $C = DO$, where O orthogonal and D diagonal and nonsingular. By assuming that the error term ε_t has independent non-Gaussian components, the orthogonal matrix O is restricted to be a permutation matrix, so only permutations and scales changes are allowed in B to achieve identification. Maximize the log-likelihood function of the model parameters in the allowed parameter space to get the maximum likelihood estimate of the parameters.

Traditional SVAR models with Gaussian errors need to limit the model parameters artificially to identify the model, and the tested constraints are required, but the strict constraints are subjective and strict, the accuracy of the constraints directly affects the analysis result of model. In general, the SVAR model assumes that the error terms have the Gaussian distribution. The SVAR model with the error terms consisting of independent non-Gaussian components can be identified without any additional restrictions, and maximize the identification of more useful economic shock information in the data, fully explain the data.

3.2. Construction of SVAR model

The identification of the non-Gaussian SVAR model described in 3.1 is achieved based on the constructed VAR(2) model object. The structural impact matrix B of the corresponding SVAR model is identified by non-Gaussian maximum likelihood. The SVAR (2) model is as follows:

$$y_t = c_t + A_1 y_{t-1} + A_2 y_{t-2} + u_t = c_t + A_1 y_{t-1} + A_2 y_{t-2} + B\varepsilon_t \tag{2}$$

where $y_t = (G_t, O_t, U_t, V_t)'$,$\varepsilon_t = (\varepsilon_G, \varepsilon_O, \varepsilon_U, \varepsilon_V)'$.

Estimated B Matrix (unique decomposition of the covariance matrix):

$$\begin{bmatrix} 0.001468798 & 0.0110944372 & -0.000784272 & 0.002320649 \\ -0.011311085 & 0.0008620552 & 0.018533089 & 0.014586421 \\ 0.001038376 & -0.0002864318 & 0.001685833 & -0.004552822 \\ 0.077294643 & 0.0045154112 & -0.005568858 & 0.002150893 \end{bmatrix}$$

Estimated standardized B matrix:

$$\begin{bmatrix} 1.0000000 & 12.8697529 & -0.4652133 & 1.078923 \\ -7.7009110 & 1.0000000 & 10.9934302 & 6.781565 \\ 0.7069559 & -0.3322662 & 1.00000000 & -2.116712 \\ 52.6244090 & 5.2379607 & -3.3033272 & 1.0000000 \end{bmatrix}$$

3.3. Impulse response function analysis

Using the impulse response function computed in the SVAR model, obtain the dynamic influence on all endogenous variables when a standard deviation impact is applied to the error term of the variables in the system, and then analysis the interaction effects between the variables.

The results of impulse response functions with 90% confidence intervals are shown in Fig. 2. The confidence intervals of impulse response functions are calculated via moving block bootstrap. The horizontal axis represents the lag time horizon of the shock, selecting observation lag of 10 (Daily). In this paper, we mainly analyze the response trajectory of the gold price returns to the shocks of each single variable, which is in the first line of Fig. 2. The gold price returns have a positive impact on its own in the first period, but the impact level has dropped rapidly, indicating that the increase in the gold price returns in the short-term will drive its returns to continue to rise, but the promotion then weaken and reach the maximum negative impact in the second period. The impact effect lasts for 5 periods, and the impact direction is constantly changing. In the long run, the impact disappears. The shocks of crude oil returns have a positive impact on gold in the first two periods, and fall to zero in the

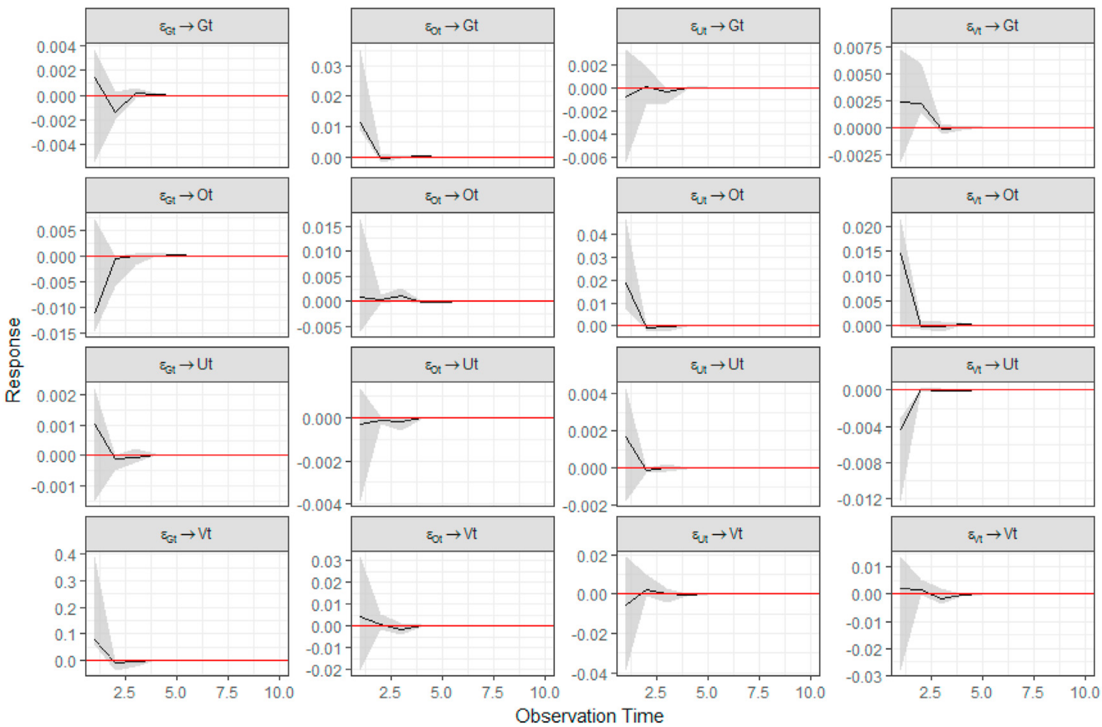

Fig. 2. Impulse response function of SVAR model.

Table 3
Forecast error variance decomposition.

Time horizon(h)	Gt	Ot	Ut	Vt
1	1.643779	93.78422	0.4686544	4.103345
2	2.890566	89.14445	0.4559871	7.509000
3	2.912332	89.02940	0.5341744	7.524091
4	2.916167	89.02624	0.5341438	7.523450
5	2.916507	89.02498	0.5342669	7.524246
6	2.916506	89.02494	0.5342804	7.524271
7	2.916507	89.02494	0.5342804	7.524272
8	2.916507	89.02494	0.5342805	7.524272
9	2.916507	89.02494	0.5342805	7.524272
10	2.916507	89.02494	0.5342805	7.524272

end of second period. The rise in crude oil returns can immediately push the gold price to rise at the highest level, but the driving force is continuously decreasing. When the crude oil market in turmoil, the market signal could be quickly transmitted to the gold market, but the impact information will be quickly digested by the market. The impact level of US dollar index continues to reduce in the 1–2 period. After the second period, the impact strength rebounded, and finally stabilized near zero in the 5 period. VIX shocks have a positive impact on the gold price returns in the 1–3 period. When the market panic spreads, it will be transmitted to the gold market quickly, pushing up the price of safe-haven assets, and the impact will gradually disappear after the third period.

On the whole, the impact of the gold market, crude oil market, US dollar index and VIX information on the gold price returns will last for about five days, that is, the gold market will digest market breaking news within 5 trading days. Crude oil has the greatest impact on gold price returns, but its duration is short. The impact of gold prices and VIX on the price of gold is relatively long.

3.4. Forecast error variance decomposition for SVAR model

Forecast error variance decomposition results of gold price returns in Table 3 show the contribution of one variable to the 1–10 step forecast error variance of the other variable, explore the degree of interaction and relative importance between different markets.

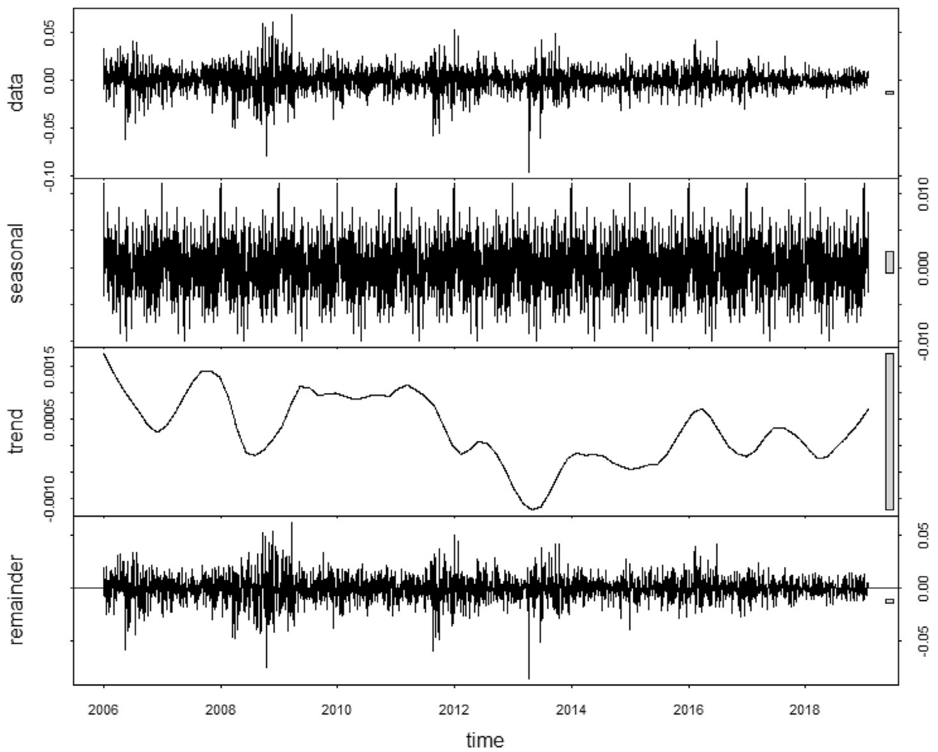

Fig. 3. STL decomposition of gold price returns.

In general, the fluctuation of the gold price returns depends to a large extent on the crude oil price returns, and has stabilized at a level of about 89% for a long time. In first horizon, it reached 93.78%, and then the intensity of interpretation decreased slightly. As an "economic barometer", the change of crude oil price will affect the market development and the degree of inflation, which conversely affects the price of gold. As closely related commodities, the shock of crude oil price returns is most important to fluctuation of gold price returns. When crude oil price changes, the time horizon of impact on the price of gold is short. The explanatory ability of VIX shock to the gold price returns continuously rising. When the VIX rises, the implied volatility of the S&P 500 index rises, and then promote the spread of market panic. During the stock market turmoil, investors are more inclined to choose safe-haven assets, which conversely push up the price of gold.

Over time, the impact of gold price returns shocks on its own returns has continued to increase, and has remained at around 2.91% for a long time. There is an inertia change in the price of gold. When the gold prices continue to rise, investors enter the gold market because of the expectation of gold appreciation and speculative psychology. At this time, the "Herd Effect" will promote market speculation and further push up the price. Such as trade disputes between China and the United States, Syrian war and other emergencies, global stock market turmoil, investors' risk aversion warmed up, gold prices continue to rise in the event fermentation. However, the macro environment in which gold faces is now more complicated, if the price of gold continues to fall due to some unexpected events, then the market is under pressure, the panic sells start in the market, most of investors will in wait-and-see state, leading to further price declines. The degree of US dollar index shock explains gold price returns is about 0.53% for a long time. During the existence of the Bretton Woods system, the price of gold was pegged to the US dollar, and after 1970s, gold began to move towards a market-oriented path. In certain period, the strength of the dollar will weaken the role of gold as a preservation and appreciation tool. However, from the perspective of the entire data period, the correlation between gold and the US dollar is weakening. When the US dollar index changes, there is a certain time-lag of effect on gold price. The rapid response of the market will digest the relevant information, making the intensity of the impact weaken.

The shock of crude oil price returns is most important to gold price returns. The contribution of the other three variables to the fluctuation of gold price returns gradually increases and eventually stabilizes.

4. Comparative analysis of gold price returns forecasting model

4.1. Technical analysis and prediction based on historical data of gold price returns

In the long run, international gold prices have been in a state of violent fluctuations. The 3257 data from January 3, 2006 to January 31, 2019 were used as a training set to model the gold price returns. The last 24 data were used as test set, and the predicted results were compared with the real values to calculate the prediction error. Quantify model accuracy and compare the accuracy between different models.

ADF test and PP test are used to test the unit root of the returns series to verify its stationarity. The results all reject the original hypothesis at the significance level of 1%, and the gold price returns series is stationary. Exponential smoothing based on Seasonal and Trend Decomposition using Loess (STL) and neural network model are used to analyze and forecast the gold price returns.

STL decomposition (Cleveland et al., 1990) based on locally weighted regression (Loess) method, the time series Y_t is decomposed into high frequency seasonal component S_{t}, low frequency trend component T_{t} and irregular/error component R_{t}, expressed as $Y_{\mathrm{t}} = S_{\mathrm{t}} + T_{\mathrm{t}} + R_{\mathrm{t}}$. The gold price returns is decomposed as shown in Fig. 3. The seasonal component shows that there is no obvious seasonal factor. Its trend component is also in a state of constant volatility. It first goes through a long period of downward trend volatility and then into uptrend volatility. The volatility of irregular component is concentrated in 2008-09, 2011-12, and 2013-14. Corresponding to the outbreak of the 2008-09 financial crisis, the United States began quantitative easing, which was stimulated by global risk aversion and hedging demand, and the price of gold prices continued to rise. The spread and escalation of the European sovereign debt crisis in 2011-12 and the geopolitical tension in the Middle East then pushed the price of gold to a historical high. In 2013-14, the United States announced to taper quantitative easing, the Syrian crisis and other events caused the gold market to fluctuate drastically.

After applying STL decomposition to the gold price returns series, the seasonal adjustment data are modeled and predicted by ETS method, and then the seasonal component prediction data and seasonal adjustment prediction data are added to obtain the final prediction results.

The ETS model is defined by three letters (Hyndman et al., 2002, 2008), which are the error component ("A", "M" or "Z"), trend component ("N", "A", "M" or "Z"), and the seasonal component ("N", "A", "M" or "Z"). In all cases, "N" means none, "A" means additive model, "M" means multiplication model, and "Z" means automatic selection. Based on the AIC information criterion, ETS (A, N, N), which is single exponential smoothing model, is finally selected to fit and predict the gold price returns. The single exponential smoothing model assumes that the observation value of returns series at time t $Y_{\mathrm{t}} = l_{\mathrm{t-1}} + \varepsilon_{\mathrm{t}}, l_{\mathrm{t}} = l_{\mathrm{t-1}} + \alpha\varepsilon_{\mathrm{t}}$, where l_{t} is the horizontal term and ε_{t} is the random term. The predicted value at t+1 time $Y_{\mathrm{t+1}} = \alpha Y_{\mathrm{t}} + \alpha(1-\alpha)Y_{\mathrm{t-1}} + \alpha(1-\alpha)^2 Y_{\mathrm{t-2}} + \ldots, 0 \le \alpha \le 1$, the closer the parameter α is to 1, the larger the recent data weight. The constructed ETS (A, N, N) model has a small α value (0.001), recent and historical information are fully taken into account in the prediction of price returns. The forecast results are shown in Table 4.

The neural network is a nonlinear network system which is connected by a large number of processing units. In recent years, the neural network model has been widely used to model and analyze time series. This paper selects a feed-forward neural network with a single hidden layer. Using the R "forecast" package, a feed-forward neural network with a structure of 35-18-1 was constructed to predict the gold price returns. The initial data is input to an input layer consisting of 35 nodes, each node is connected forward to the hidden layer and finally to the output layer with a separate node.

In this paper, the ARIMA and ETS models widely adopted in the literature are selected as benchmark models. Comparing the prediction results in Table 4, the ARIMA model has a small prediction value, and the ETS model ignored seasonality, which cannot fit the gold price returns fluctuation tendency. The predicted data loses volatility. The mean absolute error (MAE), mean squared error(MSE), root mean squared error (RMSE) of different models in Table 5, compared with benchmark models, the STL-ETS and neural network model can improve the forecast precision, and the STL-ETS model has the highest prediction accuracy, and can accurately fit the fluctuation tendency of the gold price returns. Its short-term prediction ability of gold price returns is better.

4.2. Fundamental analysis and nowcasting based on historical data of different markets

The Bayesian structural time series (BSTS) model integrates structural time series, spike and slab regression and Bayesian model averaging. The model includes trend and regression component. First, the structural time series model is used to fit the trend and seasonal, which is the trend component of the model. Then, spike-slab regression is used to select variables, which is the regression component of the model. The Markov chain Monte Carlo algorithm estimates the posterior distribution parameters of the model. Finally, the Bayesian model averaging method is used to predict(Scott and Varian, 2014). This model is a very powerful "nowcasting" system.

According to the SVAR model result in Section 3, excluding the US dollar index with the least explanation of the fluctuation of the gold price returns in our sample interval. The forecast variables of the gold price returns rate contain the crude oil price returns and VIX. The Markov chain Monte Carlo algorithm was run for 5000 iterations to construct a BSTS model to test which predictor variables were more important and predictive for gold price returns. Fig. 4 shows posterior inclusion probabilities of variables, the highest inclusion probability variable is crude oil price returns, about 1. Crude oil price returns is the most predictive variable for the gold price returns. And white bar in Fig. 4 indicates that the coefficient is positive. The VIX inclusion probability is approximately 0.26. Consistent with the results of the SVAR model, the gold price returns is positively correlated with the crude oil price returns.

Fig. 5 plots the contribution of trends, seasonal, and regression components. It contains an annual seasonal component of $S = 249$ days, with the highest seasonal component interpretation of variation. When the regression component is included in the BSTS model, the prediction interval length is the original data length. We extracted 24 days forecast data, the model can fit the trend of gold price returns in the short term. The results are shown in Table 4.

BSTS model shows that crude oil price returns have the strongest predictability to gold price returns. This is consistent with the conclusions in Section 3. The fluctuation of the gold price returns mainly depends on the shocks of the crude oil market. However, due to the complexity of market information transmission, the inclusion of more information will reduce the accuracy of short-term prediction of gold price returns.

Table 4
Forecast results of different model.

Date	Actual value	ARIMA(1,0,0)	ETS(A,N,N)	STL-ETS	Neuralnetwork	BSTS
2019/2/1	−0.00344	0.00001	0.00029	0.00096	−0.00086	0.01328
2019/2/4	−0.00498	0.00000	0.00029	0.00203	0.00143	0.00389
2019/2/5	0.00156	0.00000	0.00029	0.00247	−0.00219	−0.00343
2019/2/6	−0.00137	0.00000	0.00029	0.00079	0.00099	0.00576
2019/2/7	−0.00183	0.00000	0.00029	0.00657	0.00386	0.00031
2019/2/8	0.00370	0.00000	0.00029	0.00150	0.00020	−0.00023
2019/2/11	−0.00645	0.00000	0.00029	−0.00305	−0.00020	0.00843
2019/2/12	0.00275	0.00000	0.00029	0.00647	−0.00050	0.00118
2019/2/13	0.00214	0.00000	0.00029	0.00048	−0.00230	0.00595
2019/2/14	−0.00103	0.00000	0.00029	−0.00014	0.00063	0.00025
2019/2/15	0.00388	0.00000	0.00029	−0.00209	−0.00136	0.00385
2019/2/19	0.01328	0.00000	0.00029	0.00556	0.00123	0.00046
2019/2/20	0.00717	0.00000	0.00029	0.00440	0.00113	0.01152
2019/2/21	−0.00935	0.00000	0.00029	−0.00754	−0.00023	0.00647
2019/2/22	−0.00165	0.00000	0.00029	0.00110	−0.00282	0.00235
2019/2/25	0.00150	0.00000	0.00029	0.00593	−0.00083	−0.00041
2019/2/26	−0.00452	0.00000	0.00029	−0.00008	−0.00203	−0.00168
2019/2/27	−0.00166	0.00000	0.00029	0.00074	−0.00171	−0.00697
2019/2/28	−0.00280	0.00000	0.00029	0.00049	0.00291	0.00411
2019/3/1	−0.00547	0.00000	0.00029	−0.00297	0.00029	0.00600
2019/3/4	−0.02044	0.00000	0.00029	−0.00276	0.00088	−0.01118
2019/3/5	−0.00125	0.00000	0.00029	0.00079	−0.00026	−0.00066
2019/3/6	0.00160	0.00000	0.00029	0.00649	0.00171	0.00132
2019/3/7	−0.00043	0.00000	0.00029	−0.00681	0.00324	−0.00658

Table 5
Forecast precision of different models.

Model	MAE	MSE	RMSE
ARIMA(1,0,0)	0.00434	0.00004	0.00623
ETS(A,N,N)	0.00442	0.00004	0.00629
STL-ETS	0.00423	0.00003	0.00554
Neural Network	0.00483	0.00004	0.00653
BSTS	0.00613	0.00006	0.00787

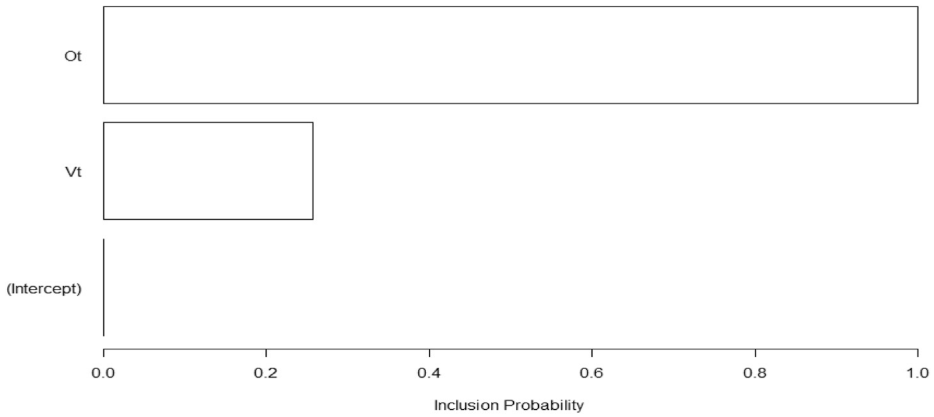

Fig. 4. Posterior inclusion probabilities.

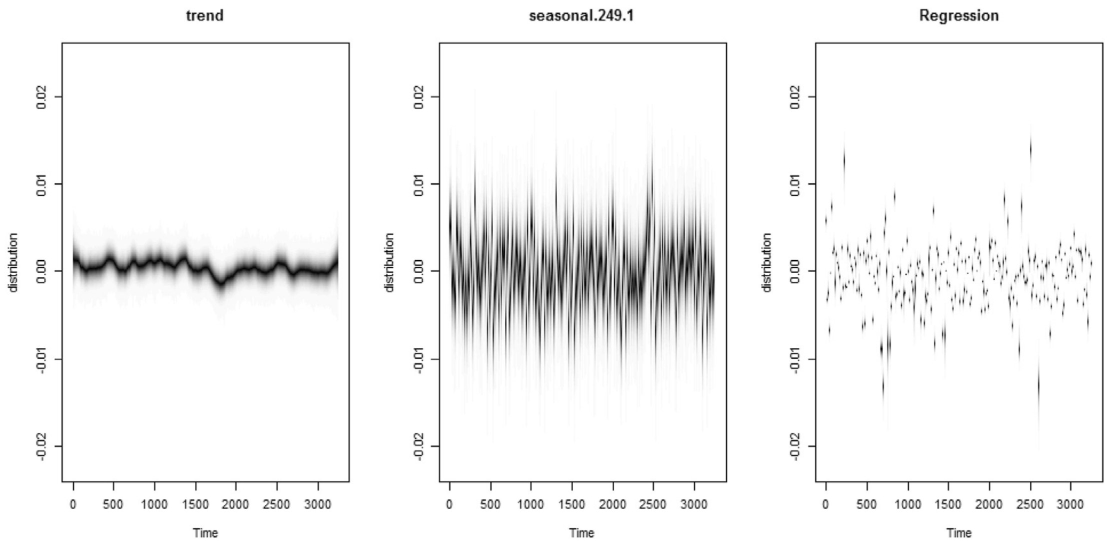

Fig. 5. State decomposition.

5. Conclusion

Gold has the dual attributes of currency and commodity. It has high liquidity and low risk. It is a popular hedging tool in the risk aversion period. This paper first constructs the VAR model of gold price, crude oil price returns, the US dollar index and VIX volatility, and then uses the non-Gaussian SVAR identification method proposed by Lanne et al. (2017) to identify the SVAR model. Based on the constructed SVAR model, the impulse response function and forecast error variance decomposition are used to analysis the dynamic relationship between gold, crude oil, the US dollar index and VIX. The impulse response function indicates that the crude oil price returns and VIX have a positive impact on the gold price returns, the US dollar index volatility has a negative impact, and the gold price returns impact direction is constantly fluctuating. The forecast error variance decomposition shows that the shocks of the crude oil price returns explains the fluctuation of the gold price returns as high as 89%. Secondly, we compared different prediction model for the gold price returns, the volatility of the US dollar index with less contribution is removed, then the gold price forecasting model is compared and analyzed through two perspectives. In the technical and the fundamental forecast models which based on the historical data of returns, STL-ETS model is more suitable for short-term forecasting of gold price returns. Based on the analysis results of this paper, the following suggestions are given:

1) For market investors, it is necessary to comprehensively determine their investment strategies based on the model prediction results and recent market conditions, focusing on gold prices, crude oil prices and market emergencies. First, the historical data of gold prices shows that in recent years, it has been in a period of upward volatility. According to the data from World Gold Council, the spot price of LBMA gold in 2016 increased 85.9 dollars per troy ounce, an increase of about 8.1%. In 2017, gold spot price rose by 145.1 dollars per troy ounce, about 12.7%. In 2018, the international political economy faced increasing challenges, and the price of gold began to fall after two years rising, however, the annual decline is only 0.01%; Until October 31, 2019, the increase of gold prices is about 18.14%. Secondly, the change of monetary policy has always been the focus of the market. In 2018, the US dollar has been one of the leading factors influencing gold prices. The gradual increase in interest rates has made the US dollar strong and has a negative impact on the gold market. Under the strong pressure of the US dollar, the price of gold began to fall from mid-April in 2018. In 2019, international monetary policy tended to be loose, the Federal Reserve cut interest rates three times during the year and the European Central Bank restarted quantitative easing, which supported the rising gold price. Finally, there are still many uncertain factors in the trade disputes between China and the United States. If the trade disputes are continue eased through business negotiations, the hedging attribute of gold will be weakened.
   Before investing, investors need to clarify their risk tolerance and expectation, conduct a rational analysis of current market conditions, and identify the main influencing factors of gold price within the interval. In the turbulent market environment, investors can consider reasonable increase of gold investment in their portfolio, diversify investment risks, and the proportion of gold allocation depends on the risk preference of portfolio.
2) For the country, gold is national strategic investment asset. Gold reserves play an important role in the national economic stability. Central banks are actively storing gold. According to the latest official gold reserve data from World Gold Council, the Russian central bank has increased its holdings of gold every year since 2006, a total of 1583.2 ounces had been increased until September 2018. After 2003, China first increased its holdings of 454.1 ounces in April 2009, and increased its holdings by 708.2 ounces in 2015. In 2016, it increased its holdings by 80.2 ounces. Until September 2018, China's gold reserves were 1842.6 tons, ranking seventh in the world, with gold accounting for 2.3% of the total foreign exchange reserves. The United States (8133.5 Tonnes), Germany (3369.9 Tonnes) and Italy (2451.8 Tonnes) are the major gold reserve countries. As the uncertainty of financial market increases, the central bank can increase its gold reserves in a timely manner and increase its share in foreign exchange reserves.
3) For producers, on the one hand, gold mining projects have a long life cycle, and it takes about several decades from exploration to post-closure. Gold mining output is not sensitive to price changes. Due to the nature of its own production, producers cannot adjust their production in time according to market demand. On the other hand, gold mine output has increased in recent years, and the data from World Gold Council shows that about 75% of the gold supply comes from gold mine production per year. The top three gold production in 2017 were China (429.4 Tonnes), Australia (289.0 Tonnes) and Russia (272.3 Tonnes). The gold mining industry is more subject to ecological and social political constraints, and the scarcity of resources has led to a decline in the quality of gold mines in some areas (Verbrugge and Geenen, 2018). With the increasing cost of gold mining, gold miners should have a long-term understanding and analysis of gold supply and demand and related market conditions. Gold prices fluctuate more frequently, in order to minimize the possible losses caused by price fluctuations, hedging can be carried out in the futures market to control its risks.

Declaration of competing interest

The authors declare no conflict of interest.

Acknowledgments

We would like to thank editors and anonymous reviewers for their valuable comments and suggestions which have significantly improved this paper. This work is supported by the National Natural Science Foundation of China (NSFC) (71874133), and the Annual Basic Scientific Research Project of Xidian University (2019).

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