The Effect of the CBOE Volatility Index (VIX) on Precious Metals Futures Prices

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Abstract

We examine the influence of the CBOE Volatility Index (VIX) on precious metals futures prices, focusing on whether market volatility affects gold price movements. Using daily data spanning 1990 to 2024, we apply regression models to explore the relationships between VIX metrics—price, change, and high values—and gold settlement prices. While significant associations are identified, with some VIX metrics exhibiting both positive and negative effects on gold prices, the model's low explanatory power (R-squared = 0.1592) limits its predictive reliability. Diagnostic tests highlight issues of heteroskedasticity, multicollinearity, and non-normal residuals, suggesting limitations in the model's specification. Despite these challenges, the findings contribute to the understanding of volatility's role in precious metals pricing and emphasize the need for more robust frameworks that address these statistical shortcomings. Future research should integrate additional market variables and refined methodologies to better capture these complex relationships.

Introduction and Importance

It is very difficult to predict the future prices of precious metals trading in the secondary financial markets. This prediction challenge can lead firms to over- or under-produce goods based on forecasted precious metals price information, leading to supply shortages or surpluses in the U.S. economy. Billah et al. (2024) explain that numerous factors make it difficult to predict financial asset prices, such as the performance of their underlying industry, unanticipated geopolitical events, general economic conditions, politics, and more. More specifically, Liberda (2017) explains that understanding precious metals price changes are complicated because their contracts lack intrinsic value and the markets precious metals contracts trade on have only been recently financialized, in comparison with stock and bond markets. Another trouble with forecasting future asset prices is that nonpublic market-moving information is often privy to specific investors, such as senators and congress members, before it is available to others. Politicians often trade on private information that will affect firms, industries, the economy in the future, and even asset prices, such as gold futures (Karadas et al., 2021). In market terms, Karadas et al. (2021) find that senators and congress members trade on nonpublic economic information before other market participants, increasing their returns over other investors (2022). Using regression analyses, Ziobrowski et al. (2017) found that Senators outperform the market by 97 basis points (.97%) on a monthly basis. These trades that are enacted on nonpublic information before other investors have access to this news skews asset prices and complicates computing future prices. Therefore, it is important for the government to restrict individuals from trading on nonpublic, market-moving information (as per securities law) and for investors to utilize ethical trading strategies that rely on statistics to predict the value of future asset prices. By understanding the relationship between various market indicators, investors can improve their financial “reward” given the level of risk they take, and still gain returns that adhere to U.S. securities law. A stronger understanding of the statistical relationship between the CBOE Volatility Index (VIX) prices and precious metals futures would allow investors holistically to predict the future price of precious metals based on the current price of the VIX. Discovering a relationship between VIX prices and gold futures would be the first step in understanding a potential causal relationship among the two, which could one day allow investors to anticipate precious metals prices given VIX prices. This paper will merely observe whether there is a relationship between the VIX and precious metals futures prices.

Literature Review

Prior studies have made a concentrated attempt to determine the causal relationship between the CBOE Volatility Index and precious metals prices; nonetheless, the empirical findings remain unclear. In one regard, Luu Duc Huynh (2020) finds that there is indeed a relationship between VIX market prices and precious metals prices. Badshah et al.'s (2013) study observed strong unidirectional, spillover effects from VIX to GVZ (CBOE's Gold Volatility Index). On the other hand, Hood & Malik (2013) assert that gold, unlike other precious metals, serves as a weak safe haven for the US stock market, given increased VIX prices. Chaudhry & Bhargava (2020) find that the persistence of volatility is asymmetric for silver and platinum; positive shocks in the VIX Index had a larger effect on silver and platinum precious metals prices when compared against a negative shock. To calculate the possible effect of VIX price movement on gold futures prices (ticker GC00), more research is required.

Empirical Model

Linear regression is used to estimate the relationship between the CBOE Volatility Index and Gold Futures prices. In this paper we estimate the following regression model:

$$\text{GoldSettlementPrice} = \alpha + \beta_1\text{VixPrice} + \beta_2\text{VixChange} + \beta_3\text{VixOpen} + \beta_4\text{VixHigh} + \beta_5\text{VixLow} + u$$

In the model above, the dependent variable measures the price (in USD) of gold futures (ticker GC00) at the end of the trading day. The VixPrice variable captures the price of the VIX at the end of the trading day. The VixChange variable measures the difference between the price of the VIX at the end of the trading day and at the beginning of the trading day. This variable is negative when the price of the VIX is lower in the end of the day than in the beginning of the day. The VixHigh variable measures the highest price of the VIX traded during the trading day. VixLow captures the lowest price of the VIX traded during the trading day.

Data

This study uses daily historical market data beginning January 2, 1990, and ending October 7, 2024. Data sources for the Gold Futures (GC00) data are available at: Gold Continuous Contract Price History | FactSet. CBOE Volatility Index price data are available at: CBOE Volatility Index Price History | FactSet. For both data sources, FactSet tracks moving market prices during every trading day (Monday – Friday, 9:30 AM – 3:30 PM EST) and provides a table with the relevant price figures for the trading day. The data were aggregated and exported into one spreadsheet for use in this paper.

Table 1 below presents descriptive statistics

Table 1. Descriptive Statistics

Variable	Mean (st. dev)	Minimum Value	Maximum Value
Gold Settlement Price ($)	1905.65 (227.61)	1464.90	2694.90
Vix Price ($)	21.48 (8.37)	11.86	82.69
Vix Change ($)	.0083 (2.22)	-17.64	24.86
Vix Open ($)	21.71 (8.41)	11.53	82.69
Vix High ($)	22.96 (9.38)	9.38	85.47
Vix Low ($)	20.50 (7.52)	10.62	70.37

Table 1 illustrates the descriptive statistics for the variables associated with gold settlement prices and VIX metrics. The average gold settlement price is $1905.65, with values ranging from a low of $1464.9 to a high of $2694.9, indicating substantial variability across observations. VIX price averages at $21.48, with a minimum of $11.86 and a maximum of $82.69, suggesting fluctuations in market volatility. VIX change exhibits an average near zero

($0.0083), with a range from -$17.64 to $24.86, reflecting both positive and negative daily changes. The average values for VIX open, high, and low prices are $21.71, $22.96, and $20.5, respectively, with all three metrics showing a spread from around $10 to approximately $89, indicating variation in opening, highest, and lowest prices observed in the data.

Empirical Results

Regression results in Table 2 below show that several VIX-related metrics have varying levels of association with GC00 prices. The coefficients indicate that increases in VIX price, VIX change, and VIX high significantly impact gold settlement prices, though the model's low R-squared value (0.1592) suggests limited explanatory power. Specifically, a one-unit increase in VIX price corresponds to a decrease in gold settlement price by approximately 7.86 (p-value < 0.01), while a one-unit increase in VIX change is associated with a rise in gold settlement price of 1.65 (p-value < 0.01). Additionally, VIX high shows a positive effect, with each unit increase associated with a 10.66 increase in gold price (p-value < 0.01). Other variables, such as VIX open and VIX low, do not show significant associations at the 5% level. Overall, while some relationships are statistically significant, the model's results are not robust enough to strongly conclude substantial predictive power in explaining gold settlement prices.

Table 2. Regression Results

Source	SS	df	MS
Model	10013660.5	5	2002732.09
Residual	52868610.8	1,208	43765.4063
Total	62882271.3	1,213	51840.2896

Number of obs	=	1,214
F(5, 1208)	=	45.76
Prob > F	=	0.0000
R-squared	=	0.1592
Adj R-squared	=	0.1558
Root MSE	=	209.2

goldsettle~e	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
vixprice	-7.86037	7.844635	-1.00	0.317	-23.25099	7.530252
vixchange	1.649589	5.702669	0.29	0.772	-9.538646	12.83782
vixopen	2.63325	7.537221	0.35	0.727	-12.15425	17.42075
vixhigh	10.66177	4.554468	2.34	0.019	1.726227	19.59732
vixlow	-19.11898	6.475241	-2.95	0.003	-31.82295	-6.415011
_cons	2164.569	18.44699	117.34	0.000	2128.377	2200.76

Additional Diagnostic Tests

Heteroskedasticity (White Test): Failed

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White's test
H0: Homoskedasticity
Ha: Unrestricted heteroskedasticity

   chi2(20) = 159.81
Prob > chi2 = 0.0000
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Cameron & Trivedi's decomposition of IM-test

Source	chi2	df	p
Heteroskedasticity	159.81	20	0.0000
Skewness	58.20	5	0.0000
Kurtosis	72.61	1	0.0000
Total	290.62	26	0.0000

Based on the results of the White Test, the P-value is significantly lower than 0.05 (0.0000). Consequently, we reject the null hypothesis of homoskedasticity and conclude that there is strong evidence of heteroskedasticity in the residuals. This suggests that the variance of the residuals is not constant, and further steps may be needed to address this issue, such as using robust standard errors or transforming the model.

Multicollinearity Test: Failed

Variable	VIF	1/VIF
vixprice	**119.71**	**0.008354**
vixopen	**111.61**	**0.008960**
vixlow	**65.91**	**0.015173**
vixhigh	**50.69**	**0.019727**
vixchange	**4.44**	**0.225082**
Mean VIF	**70.47**	

The results of the multicollinearity test show that several variables have VIF values significantly greater than 10, such as vixprice (119.71), vixopen (111.61), and vixlow (65.91). Since these VIF values exceed the threshold of 10, the model fails the multicollinearity test.

Test for Normality (Skewness and Kurtosis Test): Failed

Skewness and kurtosis tests for normality

				Joint test	
Variable	Obs	Pr(skewness)	Pr(kurtosis)	Adj chi2(2)	Prob>chi2
resid	**1,214**	**0.0000**	**0.0000**	**174.39**	**0.0000**

Looking at the residuals of the model, we see that the p-values for both skewness (0.0000) and kurtosis (0.0000) are significantly lower than 0.05. Additionally, the joint test for normality has a p-value of 0.0000, which is also lower than 0.05. Therefore, the residuals do not pass the normality test, indicating that they are not normally distributed. This issue should be addressed by potentially transforming the dependent variable or adjusting the regression model to account for non-normality in the residuals.

Ramsey Test: Failed

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Ramsey RESET test for omitted variables
Omitted: Powers of fitted values of goldsettlementprice

H0: Model has no omitted variables

F(3, 1205) =   8.07
  Prob > F = 0.0000
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The Ramsey RESET test helps analyze whether nonlinear combinations of the fitted values may help explain the dependent variable. Since the p-value is significant (0.0000 < 0.05) in the regression, the model fails the Ramsey Test, and we reject the null hypothesis that there is no omitted variable bias. This indicates that the model may suffer from misspecification, such as omitted variables or an incorrect functional form, which should be addressed to improve the model's accuracy.

Alternative Specifications

To correct the Normality issue shown in the Skewness/Kurtosis test and the Omitted Variable bias shown in the Ramsey Test, we ran the regression again with the natural log of the dependent variable, In(goldsettlementprice). As a result of this change, the model still did not pass the normality test and the Ramsey Test for omitted variable bias. This still does not pass the Ramsey test.

```
. regress ln_goldsettlementprice vixprice vixchange vixopen vixhigh vixlow
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Source	SS	df	MS			
				Number of obs	=	1,214
				F(5, 1208)	=	47.12
Model	2.54863554	5	.509727108	Prob > F	=	0.0000
Residual	13.0669142	1,208	.010816982	R-squared	=	0.1632
				Adj R-squared	=	0.1597
Total	15.6155497	1,213	.012873495	Root MSE	=	.104

ln_goldset~e	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
vixprice	-.0043561	.0039	-1.12	0.264	-.0120076	.0032953
vixchange	.0010598	.0028351	0.37	0.709	-.0045024	.006622
vixopen	.0011394	.0037471	0.30	0.761	-.0062122	.008491
vixhigh	.0048036	.0022643	2.12	0.034	.0003613	.0092459
vixlow	-.0083451	.0032192	-2.59	0.010	-.0146609	-.0020294
_cons	7.675602	.0091709	836.95	0.000	7.65761	7.693595

				Joint test	
Variable	Obs	Pr(skewness)	Pr(kurtosis)	Adj chi2(2)	Prob>chi2
resid_ln	1,214	0.0000	0.0000	67.16	0.0000

Limitations

This study's limitations should be noted. First, the R-squared value of our regression is low (0.1592), indicating that additional variables not captured by the VIX metrics might play a significant role in influencing gold settlement prices. Second, diagnostic tests highlight several model specification issues. The White Test for heteroskedasticity revealed significant evidence of non-constant variance in the residuals, suggesting that the results may be biased or inefficient without corrections, such as robust standard errors. Additionally, the multicollinearity test showed high Variance Inflation Factor (VIF) values for variables like vixprice (119.71) and vixopen (111.61), indicating severe multicollinearity, which can inflate standard errors and weaken the reliability of coefficient estimates.

Third, the Skewness-Kurtosis test for normality confirmed that the residuals are not normally distributed, even after applying a natural log transformation to the dependent variable. This raises concerns about the validity of inference in the regression model. Furthermore, the Ramsey RESET test for omitted variable bias was also significant, suggesting that the model suffers from misspecification, possibly due to omitted variables or an incorrect functional form.

Lastly, this analysis does not account for external economic, political, and geopolitical events that might impact precious metal prices, which could introduce error and bias. Future research could address these limitations by incorporating high-frequency or real-time data, adding relevant market variables to reduce specification errors, and exploring alternative modeling techniques that mitigate multicollinearity and heteroskedasticity. Additionally, further studies could employ machine learning models or structural econometric approaches to better capture the complex relationships between market volatility and precious metals prices.

Conclusions, and Policy Implications

The empirical results of the relationship between VIX metrics and gold settlement prices reveal some statistically significant associations but are not strong enough to confidently assert a substantial predictive power in determining future gold prices based on VIX variables. Our findings align with the broader literature suggesting that predicting future prices of precious metals remains challenging due to the influence of multiple factors, as highlighted by Billah et al. (2024) and Liberda (2017). Although certain VIX metrics, such as VIX price, VIX change, and VIX high, show significant correlations with gold settlement prices, the low R-squared value (0.1592) suggests limited explanatory capacity of these factors alone.

While this study does not establish a definitive link that could serve as a reliable predictive model, it suggests that understanding the relationship between market volatility (as measured by the VIX) and gold futures prices could be beneficial for investors. Policymakers and financial regulators may consider this relationship when formulating rules that prevent unethical trading based on nonpublic, market-moving information. Given the findings by Karadas et al. (2021) and Ziobrowski et al. (2017) regarding insider trading among politicians, ensuring a fair and transparent trading environment could help maintain market stability and improve investor confidence. Additionally, further regulations to restrict trading on nonpublic information could mitigate potential distortions in precious metal prices, benefiting the broader financial market.

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