A Note on Oil Price Shocks and the Forecastability of Gold Realized Volatility[#]

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Abstract

We examine the predictive power of disentangled oil price shocks over gold market volatility via the heterogeneous autoregressive realized volatility (HAR-RV) model. Our in- and out-of-sample tests show that combining the information from both oil supply and demand shocks with the innovations associated with financial market risks improves the forecast accuracy of realized volatility of gold. While financial risk shocks are important on their own, including oil price shocks in the model provides additional forecasting power in out-of-sample tests. Compared to the benchmark HAR-RV model, the extended model with all the three shocks included outperforms, in a statistically significant manner, all other variants of the HAR-RV framework for short-, medium, and long-run forecasting horizons. The findings highlight the predictive power of cross-market information in commodities and suggest that disentangling supply and demand related factors associated with price shocks could help improve the accuracy of forecasting models.

Keywords: Oil Shocks, Risk Shocks, Gold, Realized Volatility, Forecasting

JEL Codes: C22, C53, Q02

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1. Introduction

The role of gold as a traditional "safe haven" is well-recognized in many academic studies (e.g. Baur and Lucey, 2010; Baur and McDermott, 2010) as well as in the financial press reporting that investors are often attracted to this precious metal due to the portfolio diversification/hedging benefits it offers during periods of high economic uncertainty (Bouoiyour et al., 2018; Beckmann et al., 2019). Accordingly, given the dual nature of gold as both an investment and consumption commodity, one could argue that return volatility in gold would be highly sensitive to market shocks, driven both by commodity supply/demand related factors as well as financial market based fundamentals. In a recent study, Ready (2018) proposes a novel methodology to disentangle supply/demand related shocks in the oil market from financial market based shocks. Considering that oil market related shocks have a significant effect on macro and financial uncertainties, which in turn, affect the demand for gold as a traditional safe haven, this study explores the predictive power of oil supply/demand shocks, as proxies for commodity market shocks, and risk shocks, as a proxy for financial market shocks, over gold market volatility. By doing so, this study contributes the literature from a novel angle by examining the role of commodity supply and demand based factors as a predictor of gold market volatility, after controlling for financial market related shocks.

Clearly, accurate forecasts of gold return volatility is of paramount interest to investors and portfolio managers in their asset pricing models (e.g. gold derivatives pricing) as well as in hedging strategies to mitigate stock market risks in equity portfolios. Not surprisingly, there exists a large literature in empirical finance that aims at forecasting gold volatility (see Pierdzioch et al. 2016, and Fang et al. 2018, for detailed reviews). Considering that the information contained in intraday data leads to more precise estimates and forecasts for daily gold return volatility, as highlighted recently by Asai et al. (2019, forthcoming) and Gkillas et al. (2019), we contribute to earlier research by forecasting the realized volatility (RV) of gold returns, computed from 5-minute-interval intraday data, by employing a modified version of the popular Heterogeneous Autoregressive (HAR) model introduced by Corsi (2009). More specifically, we extend the basic HAR-RV model to incorporate information on daily shocks associated with the demand and supply related factors in the oil market, and examine the predictive power of supply/demand shocks over and above the information captured by the innovations associated with financial market risks.

The motivation to introduce oil market related supply and demand shocks into the HAR-RV model emanates from a series of recent studies (see for example, Antonakakis et al. 2014, Degiannakis et al. 2018, Hailemariam et al. 2019) demonstrating that oil shocks are a major driver of macroeconomic uncertainty, where the transmission operates via direct and indirect channels associated with investment, inflation, production, and the size of the public sector, respectively. Furthermore, Demirer et al. (2020) argue that supply and demand shocks in the oil market reflect markedly different information with demand shocks capturing information related to market sentiment regarding expectations on economic fundamentals, thus serving as a significant driver of both stock and bond returns globally. Given the role of gold as a safe-haven during periods of heightened uncertainty, which have been empirically shown to be driven by oil shocks, we hypothesize that shocks driven by the demand and supply based factors in the oil market will contain valuable predictive information over gold market volatility, thus help improve forecast accuracy. Moreover, because demand driven shocks in the oil market are likely to be associated with expansionary states in economic activity, gold is likely to be substituted by investment in conventional risky assets, which will in turn reduce the demand for gold, possibly driving gold market volatility down. The opposite might be true following supply shocks, resulting in contraction in the economy, which in turn raises the demand for gold and possibly returns and volatility. Accordingly, one can argue that supply and demand related shocks in the oil market capture markedly different information regarding market sentiment and uncertainty, which in turn, could add power to forecasting models.

In a related study, Baur (2012) documents an asymmetric response of gold returns to positive and negative shocks, implied by lower (higher) return volatility due to a decline (increase) in trading activity in the gold market, following demand and supply shocks. In the case of cross-market interactions between oil and gold, the literature offers quite a few studies that relate oil and gold prices and/or returns, however, these studies primarily take on the issue from the hedging perspective.[1] Le and Chang (2012) is the only study to show that oil shocks have a statistically significant positive effect on gold returns although this study does not decompose oil price shocks into supply and demand based components, a consideration that could be valuable given the arguments outlined earlier. To the best of our knowledge, this study is the first to analyze the role of disentangled oil price shocks for out-of-sample forecasting of daily realized gold return volatility, derived from intraday data. Our in- and out-of-sample tests show that combining the information from both oil supply and demand shocks with the innovations associated with financial market risks indeed improves the forecast accuracy of realized volatility of gold. While financial risk shocks are important on their own, including oil price shocks in the model provides additional forecasting power in out-of-sample tests. Compared to the benchmark HAR-RV model, the extended model with all the three shocks included outperforms, in a statistically significant manner, all other variants of the HAR-RV framework for short-, medium, and long-run forecasting horizons. The findings highlight the predictive power of cross-market information in commodities and suggest that disentangling supply and demand related factors associated with price shocks could help improve the accuracy of forecasting models.

We organize the remainder of our paper as follows. Section 2 outlines the data and methodologies. Section 3 presents the results and Section 4 concludes with a discussion of investment implications.

[1] See Reboredo (2013), Balcilar et al. (2019), and Tiwari et al. (forthcoming) for detailed literature reviews.

2. Data and Methodology

2.1. Data

We use intraday data on gold futures traded in NYMEX over a 24 hour trading day (pit and electronic) to calculate our daily measure of realized gold volatility (RV). The futures price data, in continuous format, is obtained from www.disktrading.com and www.kibot.com. Close to expiration of a contract, the position is rolled over to the next available contract, provided that activity has increased. We define daily returns as the end of day (New York time) price difference (close to close). In the case of intraday returns, last-tick interpolation gives 1-minute prices (if the price is not available at the 1-minute stamp, the previously available price is imputed), and finally we compute 5-minute returns by taking the log-differences of these prices, and then these returns to calculate the realized gold volatility. Kilian (2009) notes that, in order to get a more accurate assessment of oil price effects on asset markets, one has to account for the different sources of oil price fluctuations by distinguishing between supply and demand related shocks. Although the decomposition method of Kilian (2009) has been popularly used in the literature, it tends to give too much weight to oil-specific demand shocks relative to supply shocks, and the application of the model is limited to monthly frequency only. The decomposition method recently introduced by Ready (2018) overcomes these limitations by computing supply/demand related shocks based on traded asset prices, thus allowing us to perform our analysis at daily frequency.

In order to compute oil price demand/supply as well as risk shocks per Ready (2018), we collect daily price data for the world integrated oil and gas producer index, the nearest maturity NYMEX crude-light sweet oil futures contract, and the Chicago Board Options Exchange (CBOE) volatility index (VIX).[2] Following Ready (2018), we use the first nearest maturity NYMEX crude-light sweet oil futures contract as a proxy for the price of crude oil. Finally, we use the innovations in VIX, obtained as the residuals from an ARMA (1,1) model estimated for the VIX index, to capture shocks related to changes in the market discount rate that tends to co-vary with attitudes towards risk. Our analysis covers the daily period of 5th January, 2000 to 30th May, 2017, with the start and end dates governed by the availability of data on price shocks and the intraday price data on gold. Table A1 at the end of the paper (Appendix) provides the summary statistics for daily realized volatility values and the three shock series, with the time series plots presented in Figure A1.

[2] These data are all derived from the Datastream database as maintained by Thomson Reuters. The world integrated oil and gas producer index represents the stock prices of global oil producer companies and includes large publicly traded oil producing firms (i.e., BP, Chevron, Exxon, Petrobras or Repsol), but not nationalized oil producers (such as ADNOC or Saudi Aramco).

2.2. Methodologies

The econometric framework we use in our empirical analysis consists of two components. First, we rely on the methodology introduced by Ready (2018) to decompose oil price changes into demand, supply and risk driven shocks. Second, we use the HAR-RV model developed by Corsi (2009) to forecast the realized gold volatility by incorporating the information on the three shocks.

2.2.1. Identification of Oil Price Shocks

Ready (2018) defines demand shocks as the portion of returns on a global stock index of oil producing firms that is orthogonal to the innovations to the VIX. The innovations to the VIX are considered to control for aggregate changes in market discount rates that affect stock returns of oil producing companies and are used as a proxy for risk shocks. Supply shocks, in turn, are represented by the residual component of oil-price changes that is orthogonal to both demand shocks and risk shocks. To be more specific, the decomposition model by Ready (2018) takes the following matrix form:

$$X_t = AZ_t \tag{1}$$

where $X_t = \left[\Delta oil_t, R_t^{Prod}, \xi_{VIX,t}\right]'$ is a 3×1 vector, Δoil_t denotes the change in oil price in period t, R_t^{Prod} is the return on the global stock index of oil producing firms, and $\xi_{VIX,t}$ stands for the innovation to the VIX, based on an ARMA(1,1) specification. Our focus is $Z_t = [s_t, d_t, v_t]'$, which is a 3×1 vector of oil supply, demand and risk shocks represented by s_t, d_t and v_t, respectively. Finally, A is a $3x3$ matrix of coefficients defined as:

$$A = \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix} \tag{2}$$

Ready (2018) imposes the following condition to achieve orthogonality among the three types of shocks as follows:

$$A^{-1}\Sigma_X(A^{-1})^T = \begin{bmatrix} \sigma_s^2 & 0 & 0 \\ 0 & \sigma_d^2 & 0 \\ 0 & 0 & \sigma_v^2 \end{bmatrix} \tag{3}$$

where Σ_X denotes the covariance matrix of the variables in X_t, while σ_s^2, σ_d^2 and σ_v^2 are the variance of the supply, demand and risk shocks, respectively. The specification in Eq. (3) represents a renormalization of the standard orthogonalization applied to construct structural shocks in an SVAR model. Note that the volatility of oil-price shocks is not normalized to one, but, instead, the sum of the three shocks has to be, by their very construction, equal to the total variation in the oil price. This method of decomposing oil-price shocks defines an oil supply shock as the component of oil-price fluctuations that cannot be explained by changes in global aggregate demand and changes in financial-market uncertainty.[3]

[3] In a sense, one can argue that supply shocks in this framework relate to region-specific or event-specific information that cannot be accounted for by stock-market related pricing effects.

2.2.2. *Heterogeneous Autoregressive Realized Volatility (HAR-RV) Model*

Following Anderson et al., (2012), we measure the daily realized gold volatility by the median realized variance (MRV), constructed using intraday data. *MRV* is a jump-robust estimator of integrated variance computed as follows:

$$MRV_t = \frac{\pi}{6-4\sqrt{3}+\pi}\frac{T}{T-2}\sum_{i=2}^{T-1} med\left(|r_{t,i-1}|, |r_{t,i}|, |r_{t,i+1}|\right)^2 \tag{4}$$

where $r_{t,i}$ denotes intraday gold return i within day t, and $i = 1, \dots, T$ is the number of intraday gold returns within a day. Anderson et al. (2012) argue that *MRV* is less biased in the presence of market-microstructure noise than other measures of realized volatility.

In the case of forecasting analysis, we use variants of the widely-studied HAR-RV model (Corsi 2009) to model and forecast daily realized gold volatility. While the HAR-RV model apparently has a simple structure, it accounts for important properties of realized volatility such as long memory (Gil-Alana et al., 2015) and multi-scaling behavior (Wang et al., 2019), to be captured precisely. The benchmark HAR-RV model is given by:

$$RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \varepsilon_{t+h} \tag{5}$$

where the index h denotes h-days-ahead realized volatility, with $h =$ 1, 5, and 22 in our context. In addition, $RV_{w,t}$ is the average RV from day $t-5$ to day $t-1$, while $RV_{m,t}$ denotes the average RV from day $t-22$ to day $t-6$. When we add the oil supply (s) and demand (d) shocks, in addition to risk shocks (v), to the benchmark HAR-RV model, we obtain the following extended HAR-RV model, which includes oil and risk shocks in the set of predictors (Q):

$$RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta' Q_t + \varepsilon_{t+h} \tag{6}$$

where, θ and Q are $p\times1$ vectors. In our forecasting exercise, we set Q_t = [s_t]; [d_t]; [v_t]; [s_t, d_t]; [s_t, v_t]; [d_t, v_t]; [s_t, d_t, v_t] to explore variants of the HAR-RV model with various combinations of shocks included in the model. Note that, while our focus in this particular study is on oil market driven shocks given their relationship with uncertainty, interesting extensions of our analysis, based on the work by Degiannakis and Filis (2017, 2020), would be to incorporate the realized volatilities of other asset classes in the forecasting model and to evaluate forecasts using some economically motivated loss functions (e.g., loss functions derived from trading strategies based on volatility forecasts.

3. Empirical Results

Campbell (2008) points out that the ultimate test of any predictive model (in terms of the econometric methodologies and predictors employed) is in its out-of-sample performance. Given this, our focus is a forecasting exercise from an out-of-sample perspective. However, for the sake of completeness, in Table A2 (Appendix), we provide the full-sample estimation results for Eq.

(6), with $Q = [s, d, v]$ for $h = 1$, 5 and 22. Consistent with our aforementioned arguments regarding the possible behavior of gold during contractionary market states following supply shocks, we observe that oil supply and risk shocks increase realized volatility. In line with the notion that gold is a traditional safe haven for investors during periods of uncertainty, the positive effect of oil supply and risk shocks reflect the unfavorable sentiment in financial markets regarding the macroeconomic environment, which in turn, is associated with higher gold market volatility. At the same time, we find that oil demand shocks negatively affect realized gold volatility. This is in fact consistent with the finding in Demirer et al. (2020) of a positive (negative) effect of oil demand shocks on global stock (bond) markets and supports the argument that oil demand shocks capture information related to market sentiment regarding economic growth expectations. In our case, the negative effect of oil demand shocks on gold return volatility reflects the favorable sentiment captured by positive oil demand shocks, thus predicting lower gold return volatility. Finally, barring the demand shock at the one-week-ahead horizon, we observe that the shock terms in the predictive models are always significant at the highest level of significance, as are the coefficients capturing the persistence of the realized volatility.

Next, we turn our attention to the primary objective of our research, i.e., the role of oil and risk shocks in forecasting the realized gold volatility. In order to study out-of-sample predictability of RV, we consider a recursive estimation approach over the out-of-sample period, which covers the period of 20th December, 2002 to 30th May, 2017. Note that, in order to determine the out-of-sample period, we first conducted the multiple structural break tests of Bai and Perron (2003) on the HAR-RV model including all shock series, and detected the following breaks: 20/12/2002, 22/02/2006, 19/08, 2008, 27/09/2011, and 28/04/2014 for $h = 1$; 30/12/2002, 20/01/2006, 13/10/2008, 03/10/2011, and 02/05/2014 for $h = 5$; and, 20/12/2002, 15/02/2006, 17/10/2008, 27/09/2011, and 16/05/2014 for $h = 22$.[4]

The break date in late 2002 is likely due to supply disruptions in Venezuelan oil production caused by the civil unrest in the country, while the regime changes in 2008 and 2014 coincide with sharp declines in oil prices due to weakening of global demand. The structural break in late 2002 also coincides with the heightening tensions in Iraq during this period, resulting in the U.S. invasion of Iraq in early 2003. The break in 2006 is generally attributed to price increases due to a series of events such Hurricane Katrina, supply disruptions in Iraq due to its ongoing conflict and geopolitical tensions resulting from North Korea's missile launch. Finally, the break in 2011 is likely to have resulted from political turmoil in Egypt, Libya, Yemen, and Bahrain, which drove oil prices up. It must be noted that the breaks in 2008 and 2011 could also come from the risk shocks as these were the periods corresponding to the peaks of the Global Financial and the European sovereign debt crises. Given that the earliest break occurred at 20th December, 2002, we start our recursive estimation from this point onwards to compute the Mean Squared Forecast Errors (MSFEs) from the benchmark HAR-RV model and its seven possible extensions under h

[4] The discussion on the break dates that follows relies on the discussions in Baumeister and Kilian (2016).

=1, 5 and 22. We then use the MSE-F test of McCracken (2007) to compare the forecast accuracy of the extended versions of the HAR-RV models with the nested benchmark, i.e., the basic HAR-RV model in Eq. (5), which does not include any of the three shocks.

Understandably, because our focus is on the forecast errors, a better performing model is the one with a lower value of the MSFE. In Table 1, we report the out-of-sample forecasting gains from using an extended version of the HAR-RV model ($MSFE_1$) relative to the benchmark model ($MSFE_0$). Forecasting Gains (FG) are computed as:

$$FG = \left(\frac{MSFE_0}{MSFE_1} - 1\right)\times 100 \tag{7}$$

where $MSFE_0$ and $MSFE_1$ are the Mean Squared Forecast Errors (MSFEs) of the benchmark HAR-RV model (without any shocks) and its extended version, given the general forecasting model presented in Eq. (6). As mentioned earlier, we examine seven different predictor combinations where $Q_t = [s_t]; [d_t]; [v_t]; [s_t, d_t]; [s_t, v_t]; [d_t, v_t]; [s_t, d_t, v_t]$ for Models 1 to 7 respectively, with s, d and v denoting oil supply, oil demand and risk shocks, respectively. Given the formulation in Eq. (7), the gain (loss), in percentages, is indicated by a positive (negative) entry in the table.

Several conclusions can be drawn from the out-of-sample forecasting results: First, we see that all entries in the table are positive, indicating gains in forecasting accuracy from using all extended HAR-RV models with various combinations of oil and risk shocks incorporated to the model. This means that HAR-RV models which incorporate the information captured by oil price and risk shocks produce lower MSFEs relative to the benchmark HAR-RV specification.[5] Second, when considered individually, the highest forecasting gains are observed for the risk shock at h =1 and 5, and at h = 22, for the demand shock. This suggests that while financial market related shocks tend to have predictive power over shorter forecast horizons, oil demand shocks add forecasting power for gold volatility at longer horizons. One plausible argument in this regard is that risk shocks reflect short-term fluctuations in investor sentiment (or risk appetite) or perhaps reflect investors' over-reaction to information, while demand shocks reflect market's longer-term expectations regarding economic fundamentals. Nevertheless, these findings imply that risk and demand shocks capture markedly different predictive information regarding investor sentiment, which in turn, manifests itself on gold market volatility.

When we combine two shocks at a time, we observe that the best-performing models including two shock terms produce higher forecasting gains than the best-performing one shock models at respective forecasting horizons, clearly indicating that the shock terms provide additional forecasting power. Interestingly, the model that includes both demand and risk shocks produces the highest forecasting gains at the shortest and the longest horizons, while the model with supply

[5] The absolute MSFEs from the benchmark HAR-RV model at h = 1, 5 and 22 are found to be 0.93 percent, 1.57 percent and 2.16 percent, respectively. These values can, in turn, be used to recover the absolute MSFEs of the extended versions of the HAR-RV model by interested readers.

and risk shocks performs the best at $h = 5$. This is consistent with our earlier observation that the predictive power of risk (demand) shocks is concentrated on shorter (longer) forecast horizons. At the same time, we also see that the model that incorporates all three shocks outperforms all other extended HAR-RV models consistently at h =1, 5 and 22, with the highest gains obtained at the longest horizon, followed by the short- and medium-runs.[6] Clearly, both risk and oil price shocks capture predictive information over gold market volatility and including these shocks in the forecasting model results in smaller forecast errors at all forecasting horizons.

Overall, our results suggest that while risk shocks are (unsurprisingly) important on their own in forecasting realized gold volatility (given the role of gold as a safe-haven in the wake of financial market uncertainty), more accurate predictions can be obtained by supplementing the model with the information captured by oil price shocks driven by supply and demand related factors. Finally, and more importantly, the forecasting gains from all seven variants of the extended HAR-RV model are statistically significant at the 1 percent level of significance using the MSE-F statistic, confirming the robustness of the predictive information captured by these shocks. Although not explicitly reported in the table, when we compare the two best performing models at each forecast horizon, namely (i) HAR-RV with *s*+*d*+*v* vs. HAR-RV with *d*+*v* for $h=1$; (ii) HAR-RV with *s*+*d*+*v* vs. HAR-RV with *s*+*v* for $h=5$; and (iii) HAR-RV with *s*+*d*+*v* vs. HAR-RV with *d*+*v* for $h=22$, we estimate the MSE-F statistics to be 8.60, 3.54, and 12.87, respectively, again significant at the 1 percent level.[7] This result further supports our earlier conclusion that the model that incorporates all three shock terms not only statistically outperforms the benchmark HAR-RV model, but also dominates all other variations of extended HAR-RV models.

Table 1. Out-of-Sample Forecasting Gains.

	Forecasting Models						
Horizon	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
$h = 1$	0.1868*	0.9432*	1.2416*	1.1780*	1.4309*	2.1140*	2.3492*
$h = 5$	0.1460*	0.1033*	0.5891*	0.2615*	0.7350*	0.6734*	0.8305*
$h = 22$	0.2640*	1.6852*	0.7388*	2.0375*	1.0053*	2.3516*	2.7045*

Note: Entries correspond to forecasting gains, i.e., $FG = \left(\frac{MSFE_0}{MSFE_1} - 1\right) \times 100$, where $MSFE_0$ and $MSFE_1$ are Mean Squared Forecast Errors (MSFEs) of the benchmark HAR-RV model (without any shocks) and its extended version, given the general forecasting model: $RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta' Q_t + \varepsilon_{t+h}$, where $Q_t = [s_t]$; $[d_t]$; $[v_t]$; $[s_t, d_t]$; $[s_t, v_t]$; $[d_t, v_t]$; $[s_t, d_t, v_t]$ for Models 1 to 7 respectively, with s, d and v denoting oil supply, oil demand and risk shocks, respectively. For the benchmark HAR-RV model, $Q = []$; * indicates significance of the MSE-F test statistic at the 1 percent level.

[6] The relatively weaker performance at $h = 5$ is probably due to the insignificant coefficient on the demand shock, which we observe in the corresponding in-sample regression.

[7] The critical values at 10 percent, 5 percent and 1 percent are 0.1270, 1.6120, and 4.1840 respectively, as derived from Table 4 of McCracken (2007, p. 732).

4. Conclusion

The role of gold as a traditional safe-haven during periods of heightened uncertainty is well-established in the academia as well as in the financial media. Given the recent evidence that oil price shocks tend to drive uncertainty regarding economic activity as well as investor sentiment, this paper extends the literature to a novel direction by exploring the predictive power of oil demand/supply shocks as well as financial market risk shocks over the realized volatility of gold returns derived from intraday data. Utilizing a recently proposed model to decompose oil price shocks to supply and demand related components, we examine the in- and out-of-sample forecasting performance of various HAR-RV models by incorporating oil price and risk shocks as possible predictors in different combinations.

We find that all shock terms on their own, and particularly risk shocks, significantly improve the forecasting performance of the benchmark HAR-RV model that does not include the shocks. Nore importantly, we show that the forecasting performance can be significantly improved when we combine the information content of the three shock terms, suggesting that oil price demand/supply shocks as well as risk shocks capture marginal predictive information for gold market volatility. In particular, when we incorporate all three shocks simultaneously in the HAR-RV model, the framework significantly outperforms all the other variants of the HAR-RV model, consistently at short-, medium-, and long forecasting horizons. The findings highlight the importance of cross-market information, in particular oil price shocks, along with risk shocks in accurately forecasting the realized volatility of gold returns.

Given the importance of accurate volatility forecasts in the pricing of derivatives as well as the computation of optimal investment positions, our findings suggest that incorporating oil price and financial risk shocks in forecasting models can help to improve the design of hedge portfolios that include gold as a hedge against financial market risks across various investment horizons. As part of future research, it would be interesting to extend our study to other popular safe havens like U.S. Treasuries, the Swiss franc and Japanese yen, and even the cryptocurrency Bitcoin, which too has recently gained some popularity as a hedge against financial market risks.

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APPENDIX:

Table A1. Summary Statistics

Statistic	Realized Volatility	Supply Shock	Demand Shock	Risk Shock
Mean	1.2904	-0.0013	-0.0016	0.0197
Median	0.8912	-0.0036	0.0252	-0.4453
Maximum	27.9853	17.4887	9.4707	49.2950
Minimum	0.0231	-17.7642	-8.9221	-31.9383
S.D.	1.5668	2.1133	1.1786	6.5257
Skewness	6.3259	-0.0559	-0.0541	0.7858
Kurtosis	67.9455	8.4403	9.4892	7.4411
Jarque-Bera	817224.2000	5527.0550	7862.5830	4142.7630
p-value	0.0000	0.0000	0.0000	0.0000
Observations	4480			

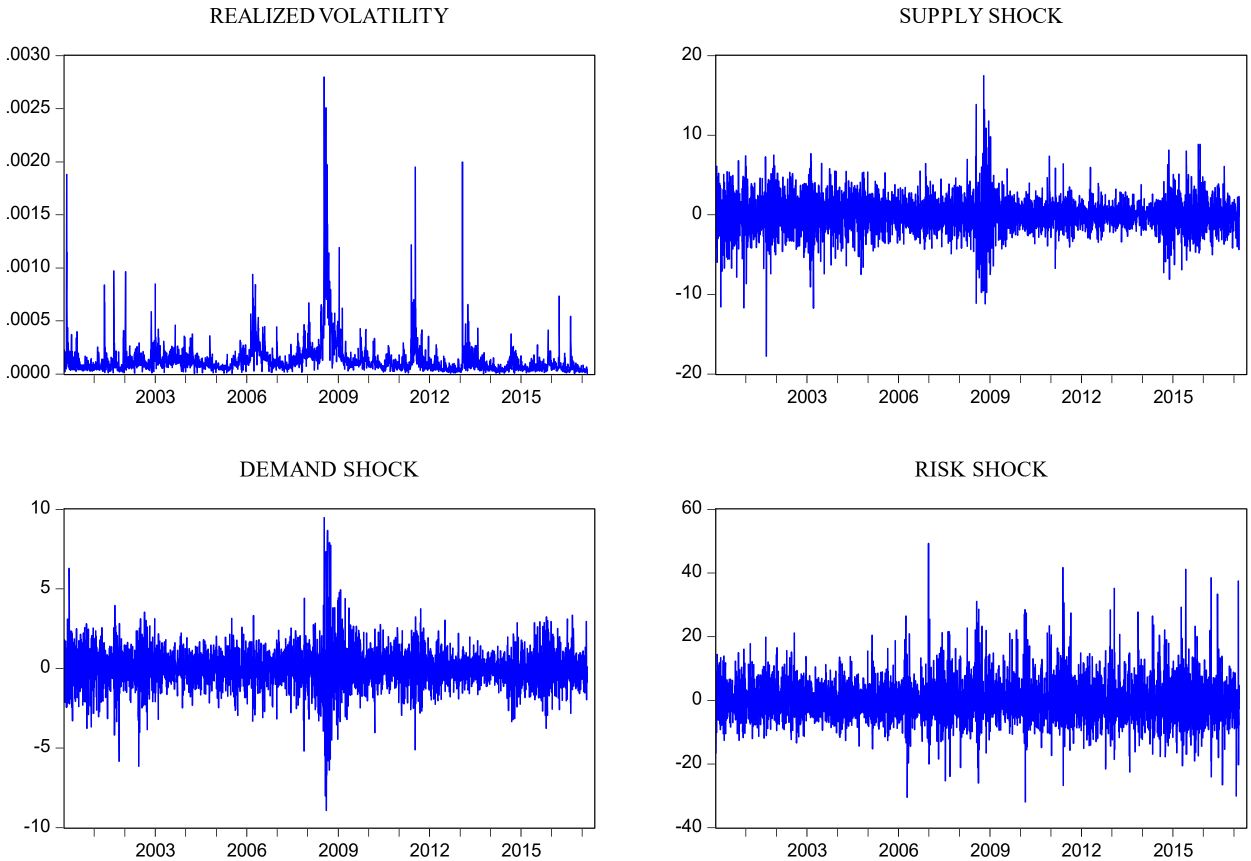
Note: S.D. stands for standard deviation; p-value corresponds to the null hypothesis of normality associated with the Jarque-Bera test.

Table A2. In-Sample Predictability Results.

Horizon	Parameter Estimate						
	β_0	β_d	β_w	β_{0m}	θ_1	θ_2	θ_3
h = 1	0.0850*	0.4711*	0.0275*	0.0147*	0.0202*	-0.0635*	0.0142*
h = 5	0.0909*	0.8631*	0.7940*	0.0043*	0.0232*	-0.0244	0.0122*
h = 22	0.0106	0.4430*	0.1108*	0.9542*	0.0409*	-0.1318*	0.0163*

Note: The table presents the estimates for: $RV_{t+h} = \beta_0 + \beta_d RV_t + \beta_w RV_{w,t} + \beta_m RV_{m,t} + \theta_1 s_t + \theta_1 d_t + \theta_1 v_t + \varepsilon_{t+h}$, where s, d and v are oil supply, oil demand and risk shocks respectively; * indicates significance at the 1 percent level.

Figure A1. Data Plots.



Note: The figures present the time-series plots for the daily realized volatility estimates for gold as well oil supply/demand and risk shocks obtained following Ready (2018).