VIX, Gold, Silver, and Oil: How do Commodities React to Financial Market Volatility?

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We examine how implied and contemporaneous equity market volatility influence gold, silver, and oil commodities futures returns. Our measure of implied volatility is the VIX index, and the measure of contemporaneous volatility uses aggregated squared intraday S&P 500 index returns. We find that Gold and silver futures returns respond to changes in implied, but not contemporaneous, volatility in a manner consistent with their properties as a safe haven. Oil has a statistically negative response to implied volatility and a marginally negative response to contemporaneous volatility. These effects are amplified during recessionary periods and robust after controlling for a dollar index.

INTRODUCTION

Gold, silver, and oil play a role in the real sector as commodities, and in the financial sector, as investment vehicles. Studies have shown that they have hedging properties with financial assets in general and equities in particular (Jaffe (1989), Giamouridis & Tamvakis (2001), and McCown & Zimmerman (2010), for example). Further work has explored the reaction of financial markets to commodity shocks (Nandha & Faff (2008), Nandha & Brooks (2009), and Mohanty & Nandha (2011), for example). Recently, Qadan & Yagil (2012) found that equity volatility leads gold returns. Beyond that, however, there is a relative dearth of studies that analyze the impact of equity market volatility on these commodities. If investors intend to use gold, silver, or oil as equity market hedges, it is important to understand the extent and timing of this impact.

While precious metals and oil have always had an exceptionally large number of industrial applications throughout the economy as a whole, these commodities have received increased scrutiny from investors over the past decade. For example, $47 billion of commodity Exchange Traded Funds (ETFs) were issued between 2008 and 2010.[1] These commodities have evolved into substitutes for equity products. Commodities (and particularly commodities futures) now serve as potential hedges from inflationary pressures; portfolio constituents for diversification opportunities; and (potentially) monetary substitutes in the event of economic turmoil. Given the myriad uses and applications for these commodities, it is critical to understand their return generating process, particularly by examining the extent to which their returns series are influenced by equity market volatility.

Our paper examines the relationship between two types of equity volatility and three commodities futures returns. Specifically, we examine the extent to which "implied" volatility (as measured by the CBOE VIX index) and "contemporaneous" volatility (constructed as an aggregation of intraday S&P 500 squared returns) relate to gold, silver, and oil futures returns. We find statistically and economically relevant relationships between gold and silver futures returns and implied, but not contemporaneous, volatility. We find a statistically significant and negative relationship between oil futures returns and implied volatility, and a marginally statistically significant negative relationship between oil futures returns and contemporaneous volatility. Our findings support the view of gold as a safe haven; oil as an inflation hedge; and silver as a pure commodity.

LITERATURE REVIEW

Many studies have examined the potential for gold as a hedge for equity investments. Jaffe (1989) finds that gold itself had a correlation close to zero with common stocks, while gold company stocks had a positive correlation with US stocks overall, over the period 1971-1987. Gold and gold stocks both had a positive correlation with the EAFE index. Faugère & Van Erlach (2005) show a relation between the real price of gold, exchange rates, and equity returns (measured by a global equity P/E ratio). Hillier, Draper & Faff (2006) show that gold and silver had negative betas to the S&P 500 over the period 1976-2004. They also find that gold was negatively correlated with the S&P 500 when realized stock market volatility (as measured by standard deviation of daily returns) was more than two standard deviations from the mean. The economic impact, however, was small. Similarly, McCown & Zimmerman (2010) find negative and significant betas for the risk premium of gold and the risk premium on US stocks (as measured by the MSCI Index minus the 30-day T-bill yield) for two- and five-year periods, and for silver over five-year periods, from 1970-2006. This result was, however, driven largely by the significance of the betas for the 1970-1979 period.

Several recent papers differentiate between gold as a safe haven and gold as a hedge. Baur & McDermott (2010) and Baur & Lucey (2010) define gold as a safe haven because it is uncorrelated with financial assets during crises, but also as a hedge because its returns are positive on average when financial asset returns are negative. Baur & McDermott (2010) use a GARCH (1,1) model and find that the return of gold is negative and significantly related to periods of high volatility, as measured by conditional volatility of an index of developed and emerging stock markets compiled by DataStream. They show that gold is also a safe haven for US stocks during the three financial crises in 1987, 1997, and 2008. Sari, Hammoudeh & Soytas (2010) also identify gold as a safe haven. Ciner, Gurdgiev & Lucey (2010) find that gold has a low correlation with the dollar and equities during periods of market distress, and that oil has also exhibited safe haven properties in the past five years.

More recent work has incorporated volatility of the commodities themselves as well as equity volatility into various econometric specifications. Baur & Lucey (2010) use asymmetric GARCH to show that gold has a negative and significant relation to equities in bear markets, but not in bull markets. Giamouridis & Tamvakis (2001) estimate an EGARCH specification (Nelson (1991)) using the Goldman Sachs and JP Morgan Commodity Indices to find that commodity returns in general display asymmetric volatility. They also find rising volatility in falling stock markets, and vice versa.

Batten, Ciner & Lucey (2010) use a monthly VAR model and find that gold volatility does not respond to changes in equity volatility, but is instead sensitive only to monetary variables during the period of 1986-1995. From 1996-2006, however, gold volatility does have a positive relation to equity volatility. The volatility of silver is not sensitive to either financial or monetary shocks in either period.

Sari, Soytas & Hacihasanoglu (2011) use a VAR model to examine the relation between VIX, oil, and metals. Using VIX as a proxy for global risk perceptions, they find that gold, exchange rates, and VIX lead oil prices. VIX and oil were negatively related. VIX had an economically significant long run effect on oil, gold, and silver, and was itself affected by oil and silver in the long run. Most other studies analyzing the relation between oil and equities to date have focused on equity as the dependent variable (Nandha & Faff (2008), Nandha & Brooks (2009), and Mohanty & Nandha (2011), for example).

Others have examined the interaction between oil and the precious metals. Hammoudeh & Yuan (2008) find persistent volatility effects of oil shocks (as well as interest rate shocks) on both gold and silver. These effects are long-lasting, as indicated by significant persistence in EGARCH (2,2) and GARCH (2,2) models. In contrast to previous studies, they find no evidence of volatility asymmetry in their study.

Prior work suggests a relation between financial market volatility (both implied and realized) and commodities. The contribution of this paper is to identify a significant relation between anticipated financial market volatility and gold, silver, and oil. This relation is robust to dollar and recessionary effects, and surpasses any reaction to realized equity volatility.

DATA AND METHODS

Data

Our dependent variables are the daily continuously compounded returns on three futures series: West Texas Intermediate (WTI) crude oil, gold and silver. We obtained daily NYMEX prices for these series over the January 2, 1990 through December 31, 2010 time period from FactSet. There are a total of 5,290 observations per series.

Our measure of implied equity volatility is the CBOE Volatility Index®, or VIX. The VIX is derived from the volatility implied from the prices of options on the S&P 500 Index.[2] Becker, Clements & White (2007) show that the VIX contains information about both past and future jump activity, and therefore has a significant relation to realized *and* future volatility. We obtained daily VIX data from the CBOE website from January 2, 1990 through December 31, 2010. If metals serve as a safe haven, we would expect the VIX to have a significant and positive impact on gold and silver (Baur & Lucey (2010)). Conversely, we expect VIX and oil to have a negative relationship, indicating its role as an inflation hedge (Sari, Soytas & Hacihasanoglu (2011)).

To construct our measure of contemporaneous volatility, described in more detail below, we obtained intraday S&P 500 Index from Tickdata, Inc. for the sample period. We sum the continuously compounded log 30-minute returns within each individual day to construct the measure of intraday volatility. Since the VIX is fundamentally a smoothed measure of volatility, we subsequently filter the resulting contemporaneous volatility series using an exponentially weighted moving average (EWMA) method. As with anticipated volatility, we expect contemporaneous volatility to have a positive relation to gold and silver, but a negative relation to oil.

Other studies, including Baur & McDermott (2010), Sari, Hammoudeh & Soytas (2010), and Ciner, Gurdgiev & Lucey (2010), among others, argue that gold possesses "safe haven" properties during times of economic or financial distress. In order to investigate such safe haven properties among all of our commodities series, we obtain recession data from the NBER.[3] We then construct a dummy variable for the recession periods in our sample. There are three recessionary cycles (1990 to 1991, 2001, and 2007 to 2009) identified in the January 1990-December 2010 period. A total of 709 (13.4%) of the 5290 observations (per commodity series) fall within an NBER-dated recession. If gold and silver act as "safe havens" in the event of economic crisis, we would expect their returns series to exhibit an additional, positive, relationship during an NBER-dated recession. If oil is an inflation proxy, its returns should be increasing in expansions and decreasing during recessions.

Our final independent variable is a dollar index. Previous studies, including Faugere and Van Erlach (2005); Tully & Lucey (2007); and Ciner, Gurdgiev & Lucey (2010) find a statistically significant relationship between commodities futures returns and exchange rates. Hammoudeh, Yuan, McAleer & Thompson (2010) show that gold volatility is sensitive to changes in the dollar/euro exchange rate: a falling dollar raises gold and silver individual and cross-volatility. Lizardo & Mollick (2010) Lizardo and Mollick (2010) show that the dollar rises against oil exporting countries' currencies and falls against importing countries' currencies when there are oil shocks. We use the Major Currencies Trade Weighted US Dollar Index of the Board of Governors of the Federal Reserve, obtained from the Federal Reserve Bank of St. Louis FRED economic database. It is constructed as a trade-weighted average of the value of

the dollar against a variety of currencies including the Euro; Japanese yen; the British pound; and four others.[4] To the extent that gold, silver, and oil have hedging properties, we would expect to see a statistically negative relationship between this dollar index and the futures returns.

TABLE 1
DESCRIPTIVE STATISTICS OF COMMODITY FUTURES RETURNS, EQUITY VOLATILITY, AND THE DOLLAR

Panel A: Full Sample					
Variable	Mean	Median	Std Dev	Min	Max
$r_{t,GOLD}$	0.024	0.000	1.014	-7.678	8.887
$r_{t,SILVER}$	0.033	0.064	1.767	-14.794	12.469
$r_{t,OIL}$	0.026	0.034	2.465	-40.048	18.970
ΔVIX_t	-0.004	0.002	0.443	-4.107	2.155
$\Delta DOLLAR_t$	0.000	-0.050	1.511	-17.360	16.540
$SPVOL_{t,\lambda=0.5}$	0.011	0.005	0.023	0.000	0.628
Panel B: Recession Only					
Variable	Mean	Median	Std Dev	Min	Max
$r_{t,GOLD}$	0.018	0.055	1.566	-7.678	8.643
$r_{t,SILVER}$	-0.054	0.072	2.477	-13.835	12.469
$r_{t,OIL}$	-0.095	0.000	4.108	-40.048	15.672
ΔVIX_t	0.010	0.027	0.615	-4.107	2.155
$\Delta DOLLAR_t$	-0.007	-0.150	2.652	-17.360	16.540
$SPVOL_{t,\lambda=0.5}$	0.029	0.012	0.053	0.001	0.628

Note: Descriptive statistics for the percentage returns of gold, oil, and silver, measured as $100 \times ln(P_t/P_{t-1})$; implied volatility measured by the CBOE VIX Index; a trade-weighted average of the value of the dollar against a variety of currencies including the Euro, Canadian dollar, Japanese yen, and the British pound, among others, obtained from the St. Louis Fed FRED Database; and contemporaneous equity volatility measured by the summation of continuously compounded log 30-minute S&P 500 returns across an individual day, filtered using an exponentially weighted moving average (EWMA) method.

Tables 1 and 2 display descriptive statistics and correlations for the full sample (Panel A of each table) and for the subsample of observations that occur during and NBER-dated recession (Panel B of each table). In Table 1, Panel A, all three commodities exhibit positive returns on average during the full 1990 through 2010 time period. From Panel B, we see that average returns for oil and silver decrease to -0.095%, and -0.054%, respectively, during the three recessionary periods of 1987, 2001, and 2007-2009. In contrast, gold futures returns decrease, but the point estimate remained positive at 0.018%, even in recessionary times. This gives preliminary evidence that gold appears to possess some degree of "safe haven" properties, while oil and silver appear to be inflation hedges during recessions. Based on the full sample median values of 0.000, 0.064, and 0.034 for gold, silver, and oil, respectively, we conclude that gold returns are positively skewed, while silver and oil are negatively skewed. During the recessions, all three commodities exhibit negative skewness.

The average daily change in implied volatility, measured by the VIX, was -0.004 over the full sample period, but increased to 0.010 during recessions, consistent the view that the VIX is a measure of fear in the financial markets, and the tendency of the VIX to increase during financial and economic crises.[5] Our realized volatility measure doubled from 0.011 over the full sample time span to 0.029 in times of

recession. Implied volatility was negatively skewed in the full sample, but positively skewed during recessions, while the realized volatility measure exhibited the opposite behavior.

TABLE 2
CORRELATIONS FOR COMMODITY FUTURES RETURNS, EQUITY
VOLATILITY, AND THE DOLLAR

Panel A: Full Sample						
Variable	$r_{t,GOLD}$	$r_{t,SILVER}$	$r_{t,OIL}$	ΔVIX_t	$\Delta DOLLAR_t$	$SPVOL_{t,\lambda=0.5}$
$r_{t,GOLD}$	1.000	0.711***	0.233***	0.056***	-0.338***	0.001***
$r_{t,SILVER}$		1.000	0.221***	-0.039***	-0.319***	-0.057***
$r_{t,OIL}$			1.000	-0.043***	-0.113***	-0.084***
ΔVIX_t				1.000	0.034***	0.094**
$\Delta DOLLAR_t$					1.000	0.024
$SPVOL_{t,\lambda=0.5}$						1.000
Panel B: Recession Only						
Variable	$r_{t,GOLD}$	$r_{t,SILVER}$	$r_{t,OIL}$	ΔVIX_t	$\Delta DOLLAR_t$	$SPVOL_{t,\lambda=0.5}$
$r_{t,GOLD}$	1.000	0.755***	0.348***	0.091***	-0.338**	-0.0001***
$r_{t,SILVER}$		1.000	0.315***	-0.068***	-0.434*	-0.087***
$r_{t,OIL}$			1.000	-0.070***	-0.176*	-0.142***
ΔVIX_t				1.000	0.109***	0.107***
$\Delta DOLLAR_t$					1.000	0.085
$SPVOL_{t,\lambda=0.5}$						1.000
Pearson correlations between the returns of gold, oil, and silver, measured as $ln(P_t/P_{t-1})$; implied volatility measured by the CBOE VIX Index; a trade-weighted average of the value of the dollar against a variety of currencies including the Euro, Canadian dollar, Japanese yen, and the British pound, among others, obtained from the St. Louis Fed FRED Database; and contemporaneous equity volatility measured by the summation of continuously compounded log 30-minute S&P 500 returns across an individual day, filtered using an exponentially weighted moving average (EWMA) method. The null hypothesis was $H_0: \rho = 0$.						

Table 2, Panels A and B, reveal that gold is positively correlated with both of our measures of volatility over the full sample time span. The correlation of gold futures returns with the VIX is 0.056 over the full sample and increases to 0.091 during recessions. The point estimates are very close to zero, but are statistically positive at the 1% level. The increase in the correlation from the full sample to the recessionary sample could be additional evidence that gold is perceived as a safe haven, with investors gravitating to gold when they perceive the future equity market volatility will increase. The correlation of gold with the contemporaneous volatility measures is 0.001, decreasing dramatically in times of recession to -0.0001. While these values are statistically different from zero at the 1% significance level, they are very small in an economic sense, which reinforces the notion that gold is viewed as a safe haven by investors in response to increases in equity market volatility. Volatility, both implied and realized, is negatively correlated with oil, also at the 1% level of significance in the full sample and in the recessionary periods. These correlations for oil also increase (in an absolute value sense) during recessions. The change in the dollar index is negatively correlated with all three commodities, although its significance diminishes from the 1% level to the 5% and 10% level for gold and oil, respectively, during recessions. Interestingly, the correlation between the dollar and the VIX are close to zero, and highly significant in both samples, but is not significant for contemporaneous volatility in either period.

The Basic GARCH Model

The following AR1-GJR-GARCH(1,1)~t model is estimated using the aforementioned daily continuously compounded futures returns, r_t:

$$r_t = \beta_0 + \beta_1 \cdot r_{t-1} + \varepsilon_t \qquad \varepsilon_t \mid \Omega_t \sim Student\left(0, \sigma_t^2\right), \tag{1}$$

where r_t is the percentage return for a particular futures series from date t-1 to t or $r_t = 100 \cdot \ln\left(P_t / P_{t-1}\right)$, and P_t denotes the closing price on day t.[6] In (1), above, β_0 is a constant, β_1 is the AR1 coefficient, Ω_t is the information set as of time t, and "Student" denotes the conditional Student-t distribution[7]:

$$\Gamma\left(\frac{\nu+1}{2}\right)\Gamma\left(\frac{\nu}{2}\right)^{-1}\left((\nu-2)\sigma_t^2\right)^{-1/2}\left(1+\varepsilon_t^2\sigma_t^{-2}(\nu-2)^{-1}\right)^{-(\nu+1)/2} \tag{2}$$

where ν is the degrees of freedom in the t-distribution and $\nu > 2$.

The model for the conditional variance, σ_t^2 is the asymmetric GJR-GARCH model of Glosten, Jagannathan & Runkle (1993):

$$\sigma_t^2 = \gamma_0 + \gamma_1 \cdot \sigma_{t-1}^2 + \gamma_2 \cdot \varepsilon_{t-1}^2 + \gamma_3 \cdot \varepsilon_{t-1}^2 \cdot I_{t-1}, \tag{3}$$

where $I_{t-1} = 1$ if $\varepsilon_{t-1} > 0$ and 0 otherwise.[8] All of the forthcoming results are obtained using Quasi Maximum Likelihood methods. We also report robust standard errors (see Bollerslev & Wooldridge (1992)).

All of the commodity variables, the dollar index, the VIX variable, and S&P 500 returns are de-seasoned using the two-step process similar to that originally proposed by Gallant, Rossi & Tauchen (1992). The commodities, dollar index and the VIX variable are regressed on a matrix of dummy variables and a time trend. The residuals are then re-scaled to have the same mean and variance of the original series for the subsequent analysis.[9]

Models Incorporating Equity Volatility and Commodities

We explore the effect of the VIX index and S&P 500 volatility on commodities during the sample period in several different ways. The first hypothesis is that gold, silver, and oil returns are related to changes in implied equity volatility. We expect that gold and silver prices should be positively related to the VIX, as investors seek the safety of gold in anticipation of rising equity market risk. If oil acts as an inflation proxy, then we would expect a decline in oil prices in response to rise in anticipated volatility in equities.

The GARCH Model with Implied Volatility

Our first hypothesis is that precious metal returns should be positively related to increases in equity volatility. For gold, this would be due to its safe haven property; for silver, it would be due to its value as a precious metal, and as a "second best" safe haven. For oil, on the other hand, we expect a negative relation, consistent with Sari, Soytas & Hacihasanoglu (2011) conjecture of rising volatility depressing global demand.

To test these hypotheses, we modify Equation (1) to include implied volatility by adding the change in the VIX index that occurs between dates t-1 and t, or ΔVIX_t:

$$r_t = \beta_0 + \beta_1 \cdot r_{t-1} + \beta_2 \cdot \Delta VIX_t + \varepsilon_t \tag{4}$$

Tully & Lucey (2007) use a power GARCH model to show that the value of gold and gold futures is more dependent on the level of the US dollar (inversely) than on British equity returns, the British pound, US interest rates, or (UK) inflation. In fact, their dollar series was the only series that had a statistically significant relationship with gold returns. They also find that gold volatility, on the other hand, is largely determined by prior period gold volatility itself. This was true both overall and during the crisis periods of 1987 and 2001. To test the degree to which (or if) our commodities futures are influenced by the dollar exchange rate, we modify Equation (4) to include our trade weighted dollar index, discussed above, and estimate the following model:

$$r_t = \beta_0 + \beta_1 \cdot r_{t-1} + \beta_2 \cdot \Delta VIX_t + \beta_{12} \cdot \Delta DOLLAR_t + \varepsilon_t \tag{5}$$

As an additional test of the safe haven hypothesis, we add an interaction term for recession with the VIX as defined the NBER. We include an interaction term for the recession and the dollar index, to control for possible differences as indicated by the correlation changes in Table 2.

$$r_t = \beta_0 + \beta_1 \cdot r_{t-1} + \beta_2 \cdot \Delta VIX_t + \beta_4 \cdot \Delta VIX_t \cdot RECESSION$$
$$+ \beta_{12} \cdot \Delta DOLLAR_t + \beta_{13} \cdot \Delta DOLLAR_t \cdot RECESSION + \varepsilon_t \tag{6}$$

where *RECESSION* is a dummy variable takes on a value of one if a particular day in the sample falls within an NBER-dated recession.

The GARCH Model with Contemporaneous Volatility
The second hypothesis is that gold, silver, and oil are each related to contemporaneous equity volatility. The relation of returns to contemporaneous volatility changes should be positive for the precious metals and negative for oil. Investors who do not anticipate equity volatility would integrate current equity market changes by increasing their demand for safer assets such as gold and silver, while reducing demand for more volatile commodities, such as oil.
To test this hypothesis, our second model substitutes contemporaneous S&P 500 index volatility into Equations (4), (5), and (6) as follows:

$$r_t = \beta_0 + \beta_1 \cdot r_{t-1} + \beta_3 \cdot SPVOL_{t,\lambda=0.5} + \varepsilon_t \tag{7}$$

where $SPVOL_{t,\lambda=0.5}$ is a realized volatility measure constructed using high frequency intraday index returns and smoothed using an Exponentially Weighted Moving Average (EWMA) method.[10] Andersen, Bollerslev, Diebold & Labys (2001), Andersen, Bollerslev, Diebold & Labys (2003), and Andersen, Bollerslev & Meddahi (2004) construct daily volatility series by summing squared intraday returns over the course of a trading day. Volatility estimates made using such methods have been shown to be more econometrically efficient and "less noisy" than estimates obtained using squared (or the absolute value of) daily returns.[11] We follow Becker, Clements & White (2007) and use an aggregation of 30-minute S&P 500 squared log-returns as our initial estimate of contemporaneous volatility, including the overnight return as the first intraday return in order to capture the full variation over the full day.
The VIX is fundamentally an average of volatility across 22 trading days. In order to make our measure of contemporaneous volatility more "on par" with the VIX, we smooth our measure of contemporaneous volatility using an Exponentially Weighted Moving Average (EWMA) method. Constructing a EWMA series involves combining values of the original series and past values of the EWMA series, or:

$$SPVOL_{t,\lambda} = \lambda \cdot SPVOL_{t-1,\lambda} + (1-\lambda) \cdot SPVOL_{t-1} \tag{8}$$

where λ is a smoothing parameter constrained to lie on the interval [0,1], $SPVOL_{t,\lambda}$ is the EWMA value of the series, and $SPVOL_t$ is the non-EWMA value of the series (i.e. the value found by aggregating the intraday log squared returns of the index). We use a value of λ=0.5, $SPVOL_{t,\lambda=0.5}$ in the forthcoming analysis, although our results are not sensitive to the actual choice of λ.[12]

The GARCH Model with Contemporaneous and Implied Volatility

The final hypothesis is that the commodity returns are related to a combination of changes in both implied and contemporaneous equity volatility. Implied volatility is a predictor of realized volatility, but there is a possibility that investors will react differently to the different signals sent by implied and contemporaneous volatilities. The inability to incorporate the information signals with perfect efficiency could result in a differential effect on returns by the two different measures of equity market volatility. The next specification, Equation, combines the models presented in Equations and above:

$$r_t = \beta_0 + \beta_1 \cdot r_{t-1} + \beta_2 \cdot \Delta VIX_t + \beta_{12} \cdot \Delta DOLLAR_t + \beta_3 \cdot SPVOL_{t,\lambda=0.5} + \varepsilon_t \qquad (9)$$

Our final model incorporates the model from equation (9) and our *RECESSION* dummy variable discussed above:

$$\begin{aligned} r_t = \beta_0 &+ \beta_1 \cdot r_{t-1} + \beta_2 \cdot \Delta VIX_t + \beta_4 \cdot \Delta VIX_t \cdot RECESSION \\ &+ \beta_{12} \cdot \Delta DOLLAR_t + \beta_{13} \cdot \Delta DOLLAR_t \cdot RECESSION \\ &+ \beta_3 \cdot SPVOL_{t,\lambda=0.5} + \beta_4 \cdot SPVOL_{t,\lambda=0.5} \cdot RECESSION + \varepsilon_t \end{aligned} \qquad (10)$$

We turn now to a discussion of the results that are obtained by estimating the econometric specifications detailed above.

RESULTS

Relation of Commodities with Implied Volatility

As reported in Table 3, the point estimates (standard errors) on our implied equity volatility are: 0.050 (0.007) for gold and 0.033 (0.012) for silver. The point estimate for the gold series is statistically positive at the 1% level, while the silver series is statistically positive at the 5% level. These results provide support for a flight-to-quality argument for gold and silver, in that an anticipated increase in equity volatility precedes higher daily futures prices, and subsequent returns, in gold and silver.

Conversely, the estimated β_2 coefficient (standard error) on oil is -0.061 (0.022), and is statistically negative at the 5% level. However, the oil price sensitivity is more economically significant than the metals result, as a one-day decrease of 0.4% (the average change in the VIX over our sample period, as shown in Table 1) would result in an annualized increase in oil prices of six basis points.[13]

The metals returns also exhibit mean reversion, as evidenced by statistically negative point estimates on the AR1 coefficients. The point estimate (standard error) of the gold series is -0.038 (0.013) and is statistically negative at the 5% level, while the point estimate (standard error) of the silver series is -0.047 (0.013) and is statistically negative at the 1% level. The point estimate on the oil series is -0.013, but with a standard error of 0.014 is not statistically different from zero, indicating no evidence of mean reversion.

TABLE 3
PARAMETER ESTIMATES FOR CHANGES IN COMMODITIES FUTURES RETURN
VERSUS CHANGES IN IMPLIED EQUITY VOLATILITY

$$r_t = \beta_0 + \beta_1 \cdot r_{t-1} + \beta_2 \cdot \Delta VIX_t + \varepsilon_t \qquad \varepsilon_t \mid \Omega_t \sim Student\left(0, \sigma_t^2\right)$$

$$\sigma_t^2 = \gamma_0 + \gamma_1 \cdot \sigma_{t-1}^2 + \gamma_2 \cdot \varepsilon_{t-1}^2 + \gamma_3 \cdot \varepsilon_{t-1}^2 \cdot I_{t-1}$$

Series Name	Gold	Silver	Oil
β_0 (x100)	0.016* (0.008)	0.048** (0.016)	0.049* (0.026)
β_1	-0.038** (0.013)	-0.047*** (0.013)	-0.013 (0.014)
β_2 (x100)	0.050*** (0.007)	0.033** (0.012)	-0.061** (0.022)
γ_0 (x10^5)	0.012** (0.004)	0.064** (0.021)	0.363*** (0.092)
γ_1	0.016*** (0.003)	0.014*** (0.003)	0.041*** (0.007)
γ_2	0.948*** (0.006)	0.953*** (0.006)	0.934*** (0.007)
γ_3	0.024*** (0.005)	0.023*** (0.005)	-0.003 (0.008)
ν	4.062*** (0.249)	4.130*** (0.245)	6.556*** (0.589)

NOTE: r_t is the daily continuously compounded return for the futures series, ΔVIX_t denotes the day-to-day change in the CBOE VIX index. Standard errors are in parenthesis and *, **, and *** denote statistical significance at the 10%, 5% and 1% percent levels, respectively.

All three of the series display strong evidence of GARCH effects: the individual point estimates of the estimated γ_1 and γ_2 coefficients are statistically positive at the 1% level for all three of our series. The gold and silver returns series (but not the oil returns series) display evidence of asymmetric volatility. The γ_3 point estimates for the gold and silver series are 0.024 with a standard error of 0.005 and 0.023 with a standard error of 0.005, respectively. Both the gold and silver γ_3 point estimates are statistically positive at the 1% level, indicating that precious metal volatilities responds more strongly to "bad news" than "good news" in their respective markets.

The leptokurtic distribution is supported in the econometric specification, as the estimated degrees of freedom of the t-distribution is statistically significant at the 1% level for all of the futures series.

Table 4 presents estimation results with the inclusion of a dollar index as a control variable. As expected, we find a statistically negative relationship between this index and our three returns series. The point estimates (standard errors) of this coefficient, β_{12}, are -0.559 (0.026) for gold; -0.777 (0.045) for silver; and -0.458 (0.063) for oil. All three of these point estimates are statistically negative at the 1% level. The implication is that a falling dollar increases the returns of all three commodities, which is consistent with Hammoudeh, Yuan, McAleer & Thompson (2010) and Sari, Soytas & Hacihasanoglu (2011). Including the dollar index variable does not, from a statistical standpoint, change our results from Table 3; the other parameters for gold and oil are largely unaffected by the inclusion of the dollar index.

TABLE 4
PARAMETER ESTIMATES FOR CHANGES IN COMMODITIES FUTURES RETURN
VERSUS CHANGES IN IMPLIED EQUITY VOLATILITY AND THE DOLLAR

$r_t = \beta_0 + \beta_1 \cdot r_{t-1} + \beta_2 \cdot \Delta VIX_t + \beta_{12} \cdot \Delta DOLLAR_t + \varepsilon_t \qquad \varepsilon_t \mid \Omega_t \sim Student\left(0, \sigma_t^2\right)$			
$\sigma_t^2 = \gamma_0 + \gamma_1 \cdot \sigma_{t-1}^2 + \gamma_2 \cdot \varepsilon_{t-1}^2 + \gamma_3 \cdot \varepsilon_{t-1}^2 \cdot I_{t-1}$			
Series Name	Gold	Silver	Oil
β_0	0.022** (0.008)	0.047** (0.016)	0.051* (0.026)
β_1	-0.046*** (0.012)	-0.049*** (0.013)	-0.016 (0.014)
β_2 (x100)	0.042*** (0.007)	0.017 (0.012)	-0.072*** (0.021)
β_{12}	-0.559*** (0.026)	-0.777*** (0.045)	-0.458*** (0.063)
γ_0 (x10^5)	0.024*** (0.006)	0.095*** (0.026)	0.409*** (0.104)
γ_1	0.017*** (0.003)	0.015*** (0.003)	0.041*** (0.008)
γ_2	0.941*** (0.006)	0.949*** (0.006)	0.933*** (0.008)
γ_3	0.028*** (0.006)	0.023*** (0.005)	-0.004 (0.010)
ν	4.010*** (0.238)	4.211*** (0.253)	6.497*** (0.792)

NOTE: r_t is the daily continuously compounded daily return for the futures series, ΔVIX_t denotes the day-to-day change in the CBOE VIX index. $\Delta DOLLAR$ denotes the continuously compounded return on the trade weighted dollar index against other major currencies. Standard errors are in parenthesis and *, **, and *** denote statistical significance at the 10%, 5% and 1% percent levels, respectively.

For example, the GARCH coefficients are all still statistically positive at the 1% level for all three commodities. The volatility asymmetry term is statistically positive at the 1% level for the gold and silver series, and is still not statistically significantly different from zero for oil. Mean reversion is still present in the gold and silver returns series, but not in the oil series. The biggest difference we observe upon including the dollar index involves the estimated coefficient on the VIX variable for the silver series. This coefficient is now 0.017 with a standard error of 0.012, and is no longer statistically significant. This might suggest that silver behaves as more of a dollar proxy with respect to financial market volatility than do gold or oil. The estimated β$_2$ coefficients for silver and oil are very similar to the ones obtained without the dollar index. The estimated β$_2$ for gold is 0.042 and is statistically significant at the 1% level. The estimated β$_2$ for the oil series is now -0.072 and, with a standard error of 0.021, is statistically negative at the 1% level, as opposed to the 5% level in the previous model.

Table 5 displays estimation results for equation (6), which incorporates the recession dummy.[14] Including the recession dummy variable does not significantly alter our results with respect to changes in implied volatility. The estimated β$_2$ coefficients for all three commodities series are slightly smaller (in

absolute terms) in this model relative to the results presented in Table 4 without the recession dummy. However, the statistical significance of the β_2 coefficients are largely unaffected. The coefficients (standard errors) for the three series are: 0.037 (0.008), 0.015 (0.014), and -0.056 (0.023) for gold, silver, and oil, respectively.[15] The point estimate for the gold series is statistically positive at the 1% level; the point estimate for the silver series is not statistically different from zero; and the point estimate for the oil series is statistically negative at the 5% significance level (as opposed to the 1% level in Table 4).

The estimated β_4 coefficients further confirm that the impact of implied volatility on the precious metals series is insensitive to whether or not the economy is in a recession. Neither gold nor silver have estimated β_4 that are statistically different from zero, which further supports gold as a sentiment indicator more than an economic one.

For oil, on the other hand, both of the recession terms are significant. The coefficient on the dollar index and recession term equals -1.058 and is statistically significant at 1%. The state of the economy does have a measurable effect on the VIX/oil relation.

The estimated β_4 coefficient for the oil series is -0.126, and is statistically significant at the 10% level. The inverse relationship with oil and implied volatility is consistent with a view of oil as an inflation proxy: when the economy is in recession (indicator = 1), oil has a more negative response to rising market volatility, while a strong economy (indicator = 0) moderates the response of oil prices to financial market shocks.

Both the dollar index and the corresponding interaction term for the dollar index and recession were negative and significant at the 1% level (as was the dollar index in Table 4) for all the commodities. While the relation between implied equity volatility and gold, silver, and oil holds regardless of the state of the economy, it is clear the dollar also plays a role.

GARCH effects are present, positive, and statistically significant at the 1% level for all three commodities. The significance and magnitude of the GARCH effects is approximately the same as without the dollar index and without the recession terms. The leptokurtic distribution is supported in the econometric specification, as the estimated degrees of freedom parameter of the t-distribution is statistically significant at the 1% level for all of the indexes.

TABLE 5
PARAMETER ESTIMATES FOR CHANGES IN COMMODITIES FUTURES RETURN VERSUS CHANGES IN IMPLIED EQUITY VOLATILITY AND THE DOLLAR CONTROLLING FOR RECESSION

$$r_t = \beta_0 + \beta_1 \cdot r_{t-1} + \beta_2 \cdot \Delta VIX_t + \beta_4 \cdot \Delta VIX_t \cdot RECESSION +$$

$$\beta_{12} \cdot \Delta DOLLAR_t + \beta_{13} \cdot \Delta DOLLAR_t \cdot RECESSION + \varepsilon_t \qquad \varepsilon_t \mid \Omega_t \sim Student\left(0, \sigma_t^2\right)$$

$$\sigma_t^2 = \gamma_0 + \gamma_1 \cdot \sigma_{t-1}^2 + \gamma_2 \cdot \varepsilon_{t-1}^2 + \gamma_3 \cdot \varepsilon_{t-1}^2 \cdot I_{t-1}$$

Series Name	Gold	Silver	Oil
β_0 (x100)	0.021** (0.008)	0.047** (0.016)	0.051* (0.025)
β_1	-0.046*** (0.012)	-0.049*** (0.013)	-0.018 (0.014)
β_2 (x100)	0.037*** (0.008)	0.015 (0.014)	-0.056** (0.023)
β_4 (x100)	0.032 (0.022)	0.005 (0.031)	-0.126* (0.057)
β_{12}	-0.526*** (0.027)	-0.739*** (0.047)	-0.356*** (0.066)
β_{13}	-0.332*** (0.084)	-0.366** (0.144)	-1.058*** (0.202)
γ_0 (x10^5)	0.023*** (0.006)	0.096*** (0.027)	0.433*** (0.106)
γ_1	0.017*** (0.003)	0.015*** (0.003)	0.042*** (0.007)
γ_2	0.940*** (0.006)	0.948*** (0.006)	0.930*** (0.008)
γ_3	0.028*** (0.006)	0.023*** (0.005)	-0.003*** (0.009)
ν	4.005*** (0.231)	4.215*** (0.254)	6.389*** (0.618)

NOTE: r_t is the daily continuously compounded daily return for the futures series, ΔVIX_t denotes the day-to-day change in the CBOE VIX index. $\Delta DOLLAR$ denotes the continuously compounded return on the trade weighted dollar index against other major currencies. *RECESSION* denotes a recessionary period in the economy, as defined by the NBER Business Cycle Dating Committee. Standard errors are in parenthesis and *, **, and *** denote statistical significance at the 10%, 5% and 1% percent levels, respectively.

Relation of Commodities with Realized Volatility

Table 6 presents estimation results for our model that incorporates the dollar index and realized S&P 500 volatility. We find no statistically significant relationship between gold, silver, or oil returns and contemporaneous equity volatility.[16] The results for contemporaneous volatility in Table 6 sharply contrast with the relation between implied volatility and the commodities that we showed in Tables 3, 4, and 5. The estimated β_3 coefficients are negative for all three series, but we cannot reject the hypothesis that the estimated β_3 coefficient is zero for gold series, and we are only able to reject it at the 10% level for our silver and oil series. In other words, there appears to be (at best) a modest statistical relationship between contemporaneous volatility and these three commodity returns. This result suggests that investors in commodities anticipate changes in equity markets (which is consistent with Batten, Ciner & Lucey (2010)) rather than react to them.

TABLE 6
PARAMETER ESTIMATES FOR CHANGES IN COMMODITIES FUTURES RETURN VERSUS CHANGES IN CONTEMPORANEOUS EQUITY VOLATILITY AND THE DOLLAR

$r_t = \beta_0 + \beta_1 \cdot r_{t-1} + \beta_{12} \cdot \Delta DOLLAR_t + \beta_3 \cdot SPVOL_{t,\lambda=0.5} + \varepsilon_t \qquad \varepsilon_t \mid \Omega_t \sim Student\left(0, \sigma_t^2\right)$		
$\sigma_t^2 = \gamma_0 + \gamma_1 \cdot \sigma_{t-1}^2 + \gamma_2 \cdot \varepsilon_{t-1}^2 + \gamma_3 \cdot \varepsilon_{t-1}^2 \cdot I_{t-1}$		
Name	Gold	Silver	Oil
β_0 (x100)	0.024**	0.071***	0.086**
	(0.010)	(0.021)	(0.032)
β_1	-0.045***	-0.049***	-0.017
	(0.012)	(0.013)	(0.014)
β_{12}	-0.569***	-0.784***	-0.445***
	(0.026)	(0.045)	(0.063)
β_3	-0.474	-2.665*	-4.673*
	(0.902)	(1.465)	(2.500)
γ_0 (x10^5)	0.025***	0.096***	0.404***
	(0.007)	(0.027)	(0.104)
γ_1	0.016***	0.015***	0.041***
	(0.003)	(0.003)	(0.007)
γ_2	0.940***	0.949***	0.932***
	(0.006)	(0.006)	(0.008)
γ_3	0.029***	0.023***	-0.002
	(0.006)	(0.005)	(0.008)
ν	4.041***	4.233***	6.630***
	(0.249)	(0.253)	(0.637)

NOTE: r_t is the daily continuously compounded return for the futures series, $SPVOL_{t,\lambda=0.5}$ denotes contemporaneous volatility measured by the summation of continuously compounded log 30-minute S&P 500 returns across an individual day, filtered with a EWMA method using a smoothing parameter of 0.5, and $\Delta DOLLAR$ denotes the continuously compounded return on the trade weighted dollar index against other major currencies.. Standard errors are in parenthesis and *, **, and *** denote statistical significance at the 10%, 5% and 1% percent levels, respectively.

As in all of the previous results, GARCH effects are present, positive, and statistically significant at the 1% level for all three commodities. The leptokurtic distribution is supported in the econometric specification, as the estimated degrees of freedom of the t-distribution are statistically significant at the 1% level for all of the commodities.

Relation of Commodities with Implied and Realized Volatility

In Table 7, we examine the effects of anticipated and contemporaneous volatility on our commodities returns. The results are largely the same as for the individual results in Tables 4 and 6. In the presence of realized changes in S&P 500 returns, the precious metals have a positive and significant relation to changes in VIX (gold at the 1% significance level; silver at 5%); oil has a negative and significant relation to changes in VIX at the 5% level. The economic significance is the same as described for Table 4 above.

TABLE 7
PARAMETER ESTIMATES FOR CHANGES IN COMMODITIES FUTURES RETURN VERSUS CHANGES IN IMPLIED AND CONTEMPORANEOUS EQUITY VOLATILITY AND THE DOLLAR

$r_t = \beta_0 + \beta_1 \cdot r_{t-1} + \beta_{12} \cdot \Delta DOLLAR_t + \beta_2 \cdot \Delta VIX_t + \beta_3 \cdot SPVOL_{t,\lambda=0.5} + \varepsilon_t \qquad \varepsilon_t \mid \Omega_t \sim Student\left(0, \sigma_t^2\right)$			
$\sigma_t^2 = \gamma_0 + \gamma_1 \cdot \sigma_{t-1}^2 + \gamma_2 \cdot \varepsilon_{t-1}^2 + \gamma_3 \cdot \varepsilon_{t-1}^2 \cdot I_{t-1}$			
Name	Gold	Silver	Oil
$\beta_0 (\times 100)$	0.024**	0.071***	0.088**
	(0.010)	(0.021)	(0.031)
β_1	-0.046***	-0.050***	-0.016
	(0.012)	(0.013)	(0.014)
β_{12}	-0.559***	-0.779***	-0.461***
	(0.026)	(0.045)	(0.064)
$\beta_2 (\times 100)$	0.042***	0.018	-0.075***
	(0.007)	(0.012)	(0.022)
β_3	-0.285	-2.697*	-5.118*
	(0.867)	(1.481)	(2.401)
$\gamma_0 (\text{x}10^5)$	0.024***	0.000***	0.000***
	(0.006)	(0.000)	(0.000)
γ_1	0.017***	0.015***	0.040***
	(0.003)	(0.003)	(0.006)
γ_2	0.940***	0.949***	0.933***
	(0.006)	(0.006)	(0.008)
γ_3	0.028***	0.023***	-0.001
	(0.006)	(0.005)	(0.009)
ν	4.009***	4.227***	6.504***
	(0.238)	(0.271)	(0.700)

NOTE: r_t is the daily continuously compounded return for the futures series, ΔVIX_t denotes the day-to-day change in the CBOE VIX index. $SPVOL_{t,\lambda=0.5}$ denotes contemporaneous volatility measured by the summation of continuously compounded log 30-minute S&P 500 returns across an individual day, filtered with an EWMA method using a smoothing parameter of 0.5, , and $\Delta DOLLAR$ denotes the continuously compounded return on the trade weighted dollar index against other major currencies. Standard errors are in parenthesis and *, **, and *** denote statistical significance at the 10%, 5% and 1% percent levels, respectively.

In the presence of implied volatility, the relation between contemporaneous volatility and precious metals is not significantly different from zero. Although the coefficient for gold does change sign and is now positive, not negative as in Table 5 is still statistically zero. The GARCH parameters are almost identical to those presented in previous tables, including the volatility asymmetry term.

Incorporating realized volatility into the model also did not change the relation for VIX to the commodities when the recession dummy was included. As in Table 5, Table 8 shows approximately the

same point estimates at the same levels of significance for gold, silver, and oil. The relation between the recession term and oil remains negative, suggesting a negative impact of anticipated inflation on oil prices during recessions. Persistence is unchanged in the presence of both realized volatility and the interaction term.

TABLE 8
PARAMETER ESTIMATES FOR CHANGES IN COMMODITIES FUTURES RETURN VERSUS CHANGES IN IMPLIED AND CONTEMPORANEOUS EQUITY VOLATILITY AND THE DOLLAR CONTROLLING FOR RECESSION

$$r_t = \beta_0 + \beta_1 \cdot r_{t-1} + + \beta_{12} \cdot \Delta DOLLAR_t + \beta_{13} \cdot \Delta DOLLAR_t \cdot RECESSION$$
$$+ \beta_2 \cdot \Delta VIX_t + \beta_{23} \cdot \Delta VIX_t \cdot RECESSION$$
$$+ \beta_3 \cdot SPVOL_{t,\lambda=0.5} + \beta_{33} \cdot SPVOL_{t,\lambda=0.5} \cdot RECESSION + \varepsilon_t$$

Name	Gold	Silver	Oil
β_0 (x100)	0.026** (0.011)	0.074*** (0.021)	0.076** (0.032)
β_1	-0.047*** (0.012)	-0.050*** (0.013)	-0.019 (0.016)
β_{12}	-0.526*** (0.027)	-0.741*** (0.047)	-0.357*** (0.066)
β_{13}	-0.330*** (0.084)	-0.365** (0.144)	-1.035*** (0.203)
β_2 (×100)	0.037*** (0.008)	0.016 (0.013)	-0.057** (0.023)
β_{23} (×100)	0.033 (0.022)	0.005 (0.031)	-0.135** (0.054)
β_3	-0.939 (1.066)	-3.350* (1.699)	-2.363 (3.327)
β_{33}	1.822 (1.621)	1.943 (2.627)	-4.861 (4.071)
γ_0 (x10^5)	0.023*** (0.006)	0.097*** (0.027)	0.435*** (0.108)
γ_1	0.016*** (0.003)	0.015*** (0.003)	0.040*** (0.011)
γ_2	0.940*** (0.006)	0.948*** (0.006)	0.930*** (0.008)
γ_3	0.028*** (0.006)	0.023*** (0.005)	0.001 (0.014)
ν	4.008*** (0.247)	4.231*** (0.266)	6.388*** (1.054)

NOTE: r_t is the daily continuously compounded return for the futures series, ΔVIX_t denotes the day-to-day change in the CBOE VIX index. $SPVOL_{t,\lambda=0.5}$ denotes contemporaneous volatility measured by the summation of continuously compounded log 30-minute S&P 500 returns across an individual day, filtered with an EWMA method using a smoothing parameter of 0.5, $\Delta DOLLAR$ denotes the continuously compounded return on the trade weighted dollar index against other major currencies. RECESSION denotes an NBER dated recessionary cycle. Standard errors are in parenthesis and *, **, and *** denote statistical significance at the 10%, 5% and 1% percent levels.

For contemporaneous volatility, the inclusion of VIX and the interaction dummies results in differences when compared with the results in Table 6. The relation between oil and realized volatility, which was previously negative and significant at the 10% level, is now not statistically significant. The contemporaneous volatility interaction with recession was not statistically significant for any of the commodities.

CONCLUSIONS

This paper examines the effect that implied and contemporaneous volatility has on the returns series of gold, silver, and oil futures over the 1990 to 2010 time span. We find strong evidence that the returns of all three commodities futures are influenced by implied volatility. Gold and silver have a positive relationship with implied volatility, supporting the idea that investors perceive precious metals as safe havens, to be purchased in anticipation of rising equity market volatility. Oil has a negative relationship with implied volatility, indicating a reaction to an anticipated decrease in demand. Our findings are robust to the inclusion of a dollar index to proxy for various macroeconomic conditions.

By contrast, contemporaneous volatility has little or no influence on the returns of any of our commodity futures series. This suggests that investors efficiently anticipate changes in the financial markets, and therefore do not have to "catch-up" in their use of commodities as an equity hedge.

As commodities have expanded their role as portfolio diversification tools, their relation to volatility in the financial markets has taken on a new relevance. This paper shows that investors have incorporated information about equity market changes into their valuation of precious metals and oil.

ENDNOTES

1. Investment Company Institute 2011 Factbook. http://www.ici.org/pdf/2011_factbook.pdf.
2. "The CBOE Volatility Index – VIX", CBOE, 2009.
3. http://www.nber.org/cycles.html
4. Loretan, Mico, "Indexes of the Foreign Exchange Value of the Dollar," *Federal Reserve Bulletin*, Winter 2005, p. 1-8. For additional details regarding the construction of the dollar index series, please see: http://research.stlouisfed.org/fred2/series/DTWEXM?cid=94
5. For example, the highest level of the VIX, 80.86, occurred at the height of the "Great Recession" in November of 2008. This was an increase of approximately 800% from the bottom over the preceding period.
6. Note that we are subsuming a commodity specific index here, and elsewhere in the paper, for notational simplicity.
7. Following convention, we estimate the inverse of the degrees of freedom, v^{-1}, in the forthcoming analysis.
8. In an (unreported) model selection and evaluation exercise, we experimented with various low-order AR models for the mean and evaluated the GARCH-t model (Bollerslev (1987)), the EGARCH model (Nelson (1991)), the Quadratic GARCH model (Sentana (1995)), and the threshold GARCH~t model (Zakoian (1994)) relative to the GJR model. Standard information criteria selected the AR1-GJR-GARCH(1,1)~t model employed herein as the best model for our purposes. We also use Ljung & Box (1978) Portmanteau tests statistics to test for eighteenth order serial correlation in the standardized ($z_t = \varepsilon_t \cdot \sigma_t^{-1}$) and squared, standardized ($z_t^2 = \varepsilon_t^2 \cdot \sigma_t^{-2}$) residuals from equation (1) through (3), above. These tests reveal that our model does, in fact, eliminate any serial correlation and volatility clustering in our data. These results are available upon request.
9. The actual matrix of dummy variables include the number of non-trading days between observation t and t-1; a day of the week dummy (excluding Wednesday); a month of the year variable (excluding June); a time trend; and a time trend squared variable.
10. We also estimate a variant of the model detailed in Equation (7) that incorporates the aforementioned *RECESSION* dummy variable. The coefficient on this dummy variable is not statistically different from zero, so we omit a discussion of the model in the interest of brevity. Results available upon request.

11. See, for example, Andersen, Bollerslev & Diebold (2009), Frijns & Margaritis (2008), and Fleming, Kirby & Ostdiek (2003), among many others, for discussions about the advantages of realized intraday volatility over traditional daily volatility measures.

12. In unreported sensitivity analysis, we experimented with a range of values for λ, including λ = 0.1, 0.3, 0.5, 0.7 and 0.9. None of the results were substantially changed by the choice of the smoothing parameter. Results are available upon request.

13. $\left[1 + \left(\left(-0.061 \cdot 0.01 \right) \cdot \left(-0.004 \right) \right) \right]^{250} - 1 = 0.06\%.$

14. The results excluding the dollar index control variable were substantially the same for the point estimates in Table 5, except that the mean reversion for oil was significant at 10%, while silver was significant at 5%. For the interaction terms, the only material differences were that for gold, the interaction term was significant at 10%; while for oil, it was not significantly different from zero. All the GARCH effects were approximately the same with and without the dollar index. A table is available upon request.

15. The coefficient on the change in VIX is shown multiplied by 100.

16. We also estimate versions of the model similar to the model presented in Table 3 (using only contemporaneous S&P 500 volatility) and Table 5 (incorporating contemporaneous S&P 500 volatility and a recession term.) The results do not differ from the results presented in Table 6. Contemporaneous volatility was not statistically significant with or without the recession term, so we do not discuss these results (which are available upon request) here.

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