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The asymmetric volatility in the gold market revisited

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HIGHLIGHTS

- We study asymmetric volatility effects in the gold futures market with intraday data.
- Rolling HAR model estimations uncover two distinct effects.
- Short-term negative semivariance plays a pervasively important role.
- Positive semivariance is very relevant in periods of rising gold prices.
- The impact of positive semivariance is dominated by longer-term volatility effects.

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ABSTRACT

Based on 13.5 years of intraday data, this paper sheds light on the inverse asymmetric volatility effect inherent in the gold market. After decomposing realized volatility into positive and negative semivariance, rolling estimations of the HAR model uncover the relative importance of the long-term positive semivariance and reveal the dynamics of the individual volatility components over time. Two effects are identified: The relevance of the short-term negative semivariance is rather pervasive while the impact of the positive semivariance is strongly correlated with the overall development of the gold market. The asymmetric nature of gold price volatility is multi-faceted and hence more complex than previously documented.

1. Introduction

That negative returns lead to higher future volatility than positive returns is a well known fact which has been confirmed for various assets and at various frequencies. Downside risk measures have a long history in finance and are brought to the high-frequency level by Barndorff-Nielsen et al. (2010) who decompose the usual realized variance into a component that relates only to positive high-frequency returns ("good volatility") and a component that relates only to negative high-frequency returns ("bad volatility"). Patton and Sheppard (2015) provide compelling evidence that negative realized semivariance is much more important for predicting future volatility than positive semivariance for stock indices and individual US stocks.

Due to its low correlation with other asset classes especially in periods of falling equity markets, gold plays an indispensable role for investors and is often referred to as safe haven.[1] This specific feature suggests a potentially different volatility behavior than depicted above—increasing gold prices may be interpreted as a signal of upcoming turbulent periods which in turn may induce uncertainty in the gold market and increase gold price volatility. The notion that positive shocks increase gold volatility by more than negative shocks is empirically observed by Baur (2012) who applies an asymmetrical GARCH model to data at daily and lower frequencies, and further confirmed with daily data by Chiarella et al. (2016). However, to date, little is known about the dynamics of this unusual asymmetric relationship. Baur (2012) and Reboredo (2013) discuss important implications of the specific nature of gold

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[1] For a comprehensive review of the Finance literature on gold, refer to O'Connor et al. (2015).

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Fig. 1. Daily closing prices of gold futures.

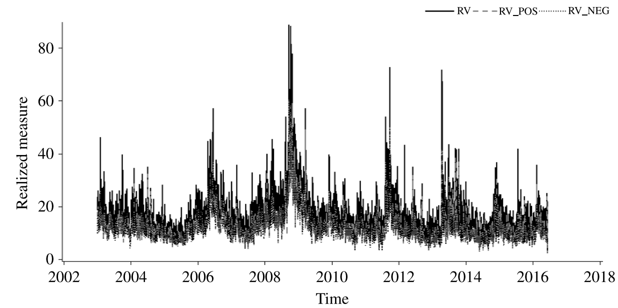

Fig. 2. Annualized daily volatility measures.

price volatility useful for portfolio diversification purposes and risk management. This in turn justifies the imperative of obtaining a profound understanding of the mechanisms underlying the volatility dynamics of the gold price.

Applying the heterogeneous autoregressive (HAR) model of Corsi (2009) to intraday data from the gold futures market over the recent 13.5 years, this study is the first to analyze the impact of positive and negative semivariance on the realized volatility of gold over different horizons. Motivated by the heterogeneity of investors, the HAR model links future volatility to historical volatility estimates aggregated over short-, mid- and long-term periods. While previous in-sample results are often restricted to a single set of point estimates, we follow a rolling window estimation approach to uncover the evolvement of the coefficient estimates over time and facilitate a deeper understanding of the mechanisms driving the volatility in the gold market.

2. Methodology

To measure the daily quadratic variation using intraday data, a realized measure is employed. Realized volatility in its original form, as proposed by Andersen and Bollerslev (1998), is obtained by the summation of squared intraday returns at the highest possible frequency. As in real world settings, the cumulative effect of microstructure issues increases with the frequency of the data, a widely established approach in literature is to base the volatility estimate on the intraday prices $P_{t,j}$ observed at time intervals of fixed length. The resultant continuous intraday returns are

$$r_{t,j} = \ln\left(\frac{P_{t,j}}{P_{t,j-1}}\right) \quad \text{for } j > 0, \tag{1}$$

with the first index t denoting the day of observation $t = 1, 2, \ldots, T$. The index j denotes the time of observation on a particular day $j = 1, 2, \ldots, J$. The realized variance on a trading day t is estimated by finding the total of the squared intraday returns,

$$RV_t = \sum_{j=1}^{J} r_{t,j}^2. \tag{2}$$

Next, RV_t is split into up- and downside realized semivariance, as proposed by Barndorff-Nielsen et al. (2010),

$$RV_t^+ = \sum_{j=1}^{J} r_{t,j}^2 I\{r_{t,j} > 0\}, \quad \text{and} \quad RV_t^- = \sum_{j=1}^{J} r_{t,j}^2 I\{r_{t,j} < 0\}, \tag{3}$$

respectively, with $RV_t = RV_t^+ + RV_t^-$. This decomposition has proved to have merits for forecasting purposes with negative semivariance containing stronger predictive power than its positive counterpart (Patton and Sheppard, 2015; Chevallier and Sevi, 2012).

Model estimations are based on the following specification of the HAR model,

$$\begin{aligned} RV_{t,t+h} &= \beta_0 + \beta_D^+ RV_{D,t}^+ + \beta_W^+ RV_{W,t}^+ + \beta_M^+ RV_{M,t}^+ + \beta_D^- RV_{D,t}^- \\ &\quad + \beta_W^- RV_{W,t}^- + \beta_M^- RV_{M,t}^- + \epsilon_t, \end{aligned} \tag{4}$$

for one-day-, one-week-, and one-month-ahead horizons ($h = 1, 5, 22$). Eq. (4) extends model (16) of Patton and Sheppard (2015) (p. 688) by decomposing weekly and monthly realized volatility into their "good" and "bad" components over short-, mid- and longer-term horizons. To obtain multi-period (weekly and monthly) volatility measures, necessary for estimating Eq. (4), we calculate a simple mean over the period of interest,

$$\sigma_{W,t} = \frac{1}{5}\sum_{i=0}^{4}\sigma_{t-i}, \quad \text{and} \quad \sigma_{M,t} = \frac{1}{22}\sum_{i=0}^{21}\sigma_{t-i},$$
$$\text{for } \sigma = RV^+, RV^-.^{2} \tag{5}$$

Results are obtained with a logarithmic variance specification since using variance in its log form does not impose non-negativity constraints for estimation purposes.

3. Data

Model (4) is applied to realized volatilities obtained from 5-minute returns of COMEX gold futures obtained from Thomson Reuters Tick History through Sirca. The original data set includes intraday observations of all existing futures contracts. The nearest month contract is rolled over to the next most liquid month when the daily volume of the current contract is exceeded. Following the COMEX contracts specifications, a trading day is defined from 6:00:00 pm ET on one day to 5:59:59 pm ET on the following day. Any entries from weekends (Friday 6:00 pm–Sunday 6:00 pm) are deleted. The sample spans the period from 2 January 2003 to 6 June 2016. Days with less than 100 observations are deleted leading to a total sample size of 3426 days.

Fig. 1 illustrates the course of gold futures prices. Daily realized volatilities and their components based on positive or negative intraday returns are shown in Fig. 2.

[2] Patton and Sheppard (2015) define weekly and monthly RV as

$$\sigma_{W,t} = \frac{1}{4}\sum_{i=1}^{4}\sigma_{t-i}, \quad \text{and} \quad \sigma_{M,t} = \frac{1}{17}\sum_{i=5}^{21}\sigma_{t-i}$$

to ease interpretation in statistical terms. We opt to keep the original specification of Corsi (2009) which allows a direct interpretation of the impact triggered by market participants acting on different time horizons.