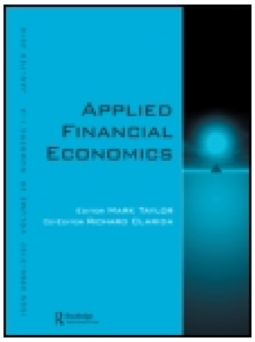

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Testing for causality between the gold return and stock market performance: evidence for 'gold investment in case of emergency'

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This article investigates the causal relationships between gold and stock market performance or uncertainty by employing nonuniform weighting cross-correlations. In our sample period covering the last decade, we detect a unidirectional causality in mean from stock to gold, but find no causality in variance between the two. For subsample periods divided into pre- and post-current financial crisis, although we detect bidirectional causality in mean for the first sample period, there exists only a unilateral causality in mean and variance from stock to gold for the second sample period. These findings imply that flight-to-quality has occurred during the recent financial turmoil.

Keywords: gold return; stock market; causality in mean; causality in variance; nonuniform weighting cross-correlations; flight-to-quality; hedge; safe haven

JEL Classification: G11; G15

I. Introduction

The main objective of this article is to elucidate the characteristics of gold as an investment asset by testing for causal relationships between the gold return and stock market performance or uncertainty over the last 10 years.

In recent years, gold price exceeded 1800 US dollars and reached its peak in nominal terms. Gold is increasingly attracting the interest of international investors as an alternative investment vehicle. What is invoking the recent surge in gold price 'seems to be a response to generalized fears of economic turmoil' (Economist, 2009). In addition, the fear of high inflation in emerging economies, such as the BRIC (Brazil, Russia, India and China) countries, and of monetary expansion (e.g. quantitative easing) in advanced countries has accelerated the sharp increase in gold price. Furthermore, gold has long been considered 'a hedge against high inflation and a weak dollar' (Economist, 2009). Gold also possesses some special properties (as does money) as a store of value, a medium for exchange and a unit of account, and it has characteristics that differ from other commodities such as crude oil, agricultural products and other precious metals.

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Like those of other goods, gold prices are determined by supply and demand. The demand for gold is roughly classified into three categories: demand for industrial use (e.g. jewellery and dental), demand for use as holdings by central banks and demand as an investment asset. With regard to the third demand type, Exchange-Traded Funds (ETFs) that index gold price have facilitated gold investments for several years. As a result, the investment demand for gold exceeded the jewellery demand in 2009, while the supply of gold has been constant or declining (Economist, 2010). As for the supply-side factors, gold is supplied by mining, scraps of gold products and sales by central banks. Despite the lack of a consensus concerning the dynamics of gold price, the behaviour of gold price deserves further attention.

However, academic research on gold is comparatively rare, even though gold is of interest to many international investors as an alternative investment. This article helps characterize gold by examining the causal relationships between the London gold return in US dollars and stock market performance or uncertainty as represented by Standard & Poor's 500 stock index (S&P 500 index). In particular, we are interested in either stock market performance or uncertainty causes flight-to-quality, more specifically, flight to gold. For this purpose, we employ the nonuniform weighting cross-correlations developed by Hong (2001). To the best of our knowledge, this work is the first to examine the causal relationships between gold and the stock market using a Cross-Correlation Function (CCF) approach. In our empirical analysis, we divide the sample into two periods to focus on the change in the role of gold as an investment asset, and we obtain results that imply a change in the relationship between gold and stock market uncertainty during the recent financial turmoil (i.e. the subprime mortgage crisis). In addition, we confirm that to some extent, these results are robust. We hypothesize that fear of financial collapse results in flight-to-quality as a hedge or a safe haven. Therefore, this article could elucidate the role of gold investments as a hedge or a safe haven during a stock market crash. However, this hypothesis does not necessarily imply that gold effectively reduces the losses incurred in a falling stock market.

The remainder of this article is organized as follows. In the next section, we review the previous research related to the present article. The data used for this analysis and the descriptive statistics are presented in Section III. In Section IV, we briefly summarize the method used to detect the existence of causality in mean and causality in variance. Section V is devoted to our empirical results. Section VI concludes.

II. Literature Review

Although the public domain contains many articles concerning gold, as described in the introduction, academic research on this issue is relatively rare. In this section, we review the previous research related to the present article.

Concerning the time series characteristics of gold price, Smith (2002) examines the random walk hypothesis for three London gold prices: AM fixing, PM fixing and closing price. The hypothesis is rejected for AM and PM fixing, but accepted for closing price. Aggarwal and Lucey (2007) show that the gold prices in round numbers become psychological barriers, such as a support and resistance levels. Their analysis suggests that this psychological factor and the specific features of gold lead to market inefficiency because if the market were efficient, such matters (i.e. psychological barriers) would not be observed. Lucey and Tully (2006) confirm that there exists daily seasonality in gold prices. According to their results, the futures market is more liquid and efficient than the cash market because there is no evidence of an abnormal pattern in the former. Furthermore, they report that the risk term is not estimated to be statistically significant in the analysis with Autoregressive Conditional Heteroscedasticity-in-Mean (ARCH-M) model, implying that the usual risk-return relationship does not hold for gold prices. Tully and Lucey (2007) use an Asymmetric Power Generalized ARCH (APGARCH) model to investigate gold price. Their results suggest that an APGARCH model including a GARCH term, a free power term and an unrestricted leverage effect term provides the most adequate description for gold return. In addition, they show that the effective exchange rate of the dollar has the most explanatory power among the macroeconomic variables on gold return.

Generally, as mentioned in the introduction, gold is viewed as a hedge against high inflation and the depreciation of the dollar. Capie *et al*. (2005) assess the role of gold as a hedge against exchange rate fluctuations in two cases: sterling pound/US dollar and yen/US dollar exchange rates. They confirm a negative and mostly inelastic relationship, in both the short- and long-run, between gold return and each of the two exchange rates using GARCH and Exponential GARCH (EGARCH) models. This relationship, however, has varied because of multiple regime shifts in the exchange rates and the prevalent political dynamics.[1]

With research goals similar to our own, Baur and Lucey (2010) analyse whether gold acts as a hedge or as a safe haven asset in the United States, the United Kingdom and Germany. In their work, a hedge is defined as an asset that is, on average, uncorrelated or negatively correlated with another asset or portfolio, while a safe haven is an asset that is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil. They find that gold is not only a safe haven for stocks in all three countries, but also a hedge in the United States and the United Kingdom. However, gold is not a safe haven for bonds in these three countries, and it is not a hedge in the United States and the United Kingdom. Furthermore, their portfolio analysis reveals that the safe haven property of gold is temporary (i.e. lasting approximately 15 trading days after the initial negative shock). Although we do not give a clear definition of hedge and safe haven in this article, our empirical results suggest that gold is indeed expected to counter stock market declines. Baur and McDermott (2010) extend the analysis of Baur and Lucey (2010). They examine the role of gold in the global financial system. According to their analysis, gold is both a hedge and a safe haven for stocks in major European countries and the United States, but not in Australia, Canada, Japan and large emerging markets such as the BRIC countries. They also argue that gold can act as a stabilizing force for the financial system by reducing losses during extreme negative shocks.[2] Do *et al.* (2009) examine the effects of return and gold volatility in London on the stock markets of five ASEAN countries: Indonesia, Malaysia, the Philippines, Thailand and Vietnam. They find that gold acts as a substitute (i.e. a countercyclical) for stocks in the Philippines and Vietnam, while it acts as a complement (i.e. a procyclical) for stocks in Indonesia, Malaysia and Thailand.

Sumner *et al.* (2010) analyse the interdependence among gold, stocks and bonds in the United States using the Spillover Index proposed by Diebold and Yilmaz (2009). They find that while return spillovers hardly occur, there is some evidence of volatility spillovers and that much of the volatility spillover is accounted for by a spillover from shocks in stocks to bonds. Because the spillover effects from gold to stocks and from gold to bonds is extremely low, they cast doubts on the forecasting power of gold for stock and bond prices. The Spillover Index is intuitive and provides useful information, but it cannot be used in hypothesis testing for causality.[3]

Lawrence (2003) investigates the relationships between gold return and such macroeconomic variables as cyclical Gross Domestic Product (GDP), long-term interest rate, short-term interest rate, rate of monetary expansion and inflation rate to test an insulation hypothesis of gold. The author reports that gold return is independent of all these macroeconomic variables, while other commodities such as West Texas Intermediate (WTI), silver and copper are affected by at least one of these variables. As a result, he suggests that gold price is also unaffected by business cycles in the United States. Kim and Dilts (2011) investigate the relationship between the value of the dollar and prices of gold and oil for monthly data. Consistent with standard economic wisdom, they find that the value of the dollar and each of the two commodities' prices have a negative relationship and that the prices of gold and oil have a positive relationship. This suggests the existence of flight-to-quality against the falling value of the dollar. Furthermore, according to their Granger causality test, a null hypothesis of no causal relationship between the value of the dollar and gold price is rejected, whereas the hypothesis for the value of the dollar and oil price is not rejected. Based on market model regressions, Hillier *et al.* (2006) explore the diversification properties of three precious metals (gold, silver and platinum) from the perspective of portfolio efficiency. They report a negative relationship between the S&P 500 index and these precious metals under a stable market with high return; they also state that all three metals function as a hedge in a volatile stock market. Furthermore, they show that these precious metals have almost no correlation with the S&P 500 index over 30 years, from 1976 to 2004, even if the sample is partitioned into subsample periods.

Gold is likely to be considered a safety net against market uncertainty. Cohen and Qadan (2010)

[1] Also refer to Joy (2011) and Pukthuanthong and Roll (2011) for the latest research on the relationship between gold and exchange rates. For the relationship between gold and inflation, refer to, for example, Mahdavi and Zhou (1997) and Worthington and Pahlavani (2007).

[2] Ciner *et al.* (2010) further extend the analysis of Baur and Lucey (2010) and Baur and McDermott (2010) by treating more asset classes (i.e. equities, bonds, dollar, oil and gold) as subjects of assessment. Chan *et al.* (2011) is the latest extensive research examining linkages between the stock market and other asset markets, covering the gold, oil, and housing markets by employing a Markov switching model.

[3] For details concerning the Spillover Index and its application to stock markets, see also Diebold and Yilmaz (2010) and Yilmaz (2010).

explicitly combine gold price and stock market uncertainty, as represented by the volatility index (VIX). VIX is often referred to as a fear gauge and is thought to reflect investor sentiment. They find that while gold price Granger-causes VIX during volatile periods, there is significant bidirectional causality between both variables during stable periods. Therefore, they conclude that investors still consider gold a substitute investment in the presence of high stock market uncertainty. Sari *et al*. (2011) is another recent work that combined gold price with VIX. They explore the information transmission mechanism between Brent oil, gold, silver and the US dollar/euro exchange rate and VIX as a proxy representing global risk perceptions. They discover only one cointegrating vector, that is, a unique long-run equilibrium relationship among these variables and also demonstrate that VIX has a significant negative effect on Brent oil in the long-run. Moreover, their analysis shows that the effect of VIX on gold price is negligible from a forecast error variance perspective and that VIX has a similar effect on gold price from an impulse response perspective.

Using the CCF approach, Bhar and Hamori (2004) examine the pattern of information flow between price changes and trading volumes in gold futures contracts. They find evidence of strong contemporaneous and moderate lagged causality in variance from price change to trading volume. Because this behaviour of gold futures is different from that reported for other commodity futures such as agricultural products and crude oil, they hypothesize that this behaviour is probably attributable to the special nature of gold as a commodity and that the importance of the gold market increases during a stock market slump. The test procedure which they use – the CCF approach developed by Cheung and Ng (1996) – is revised to incorporate nonuniform weighting by Hong (2001); we adopt Hong's approach to test for causality between gold returns and the S&P 500 index.[4]

III. Data and Descriptive Statistics

Data

We construct the daily PM fixing of London gold price in US dollars per troy ounce. The London gold fixing is the spot price of gold and determined twice, at 10:30 am and 3:00 pm, in a business day.[5] The London gold fixing is considered a worldwide benchmark for various gold prices. The data are from the London Bullion Market Association (LBMA) homepage.[6] When the PM fixing price is not available, we replace the data with next opening day's AM fixing price.

As noted at the beginning of this article, we use the daily closing value of the S&P 500 index as a variable representing stock market performance or uncertainty. Accordingly, our analysis is primarily based on the perspective of the US investors. We obtain the S&P 500 index data from the Federal Reserve Bank of St. Louis homepage.[7]

In this study, the sample period is from 4 January 2000 to 28 April 2011, and the number of observations is 2833. Figure 1 illustrates that the time series behaviour of the PM fixing of the London gold price and the closing value of the S&P 500 index. Over the sample period, the gold price appears almost monotonically increasing, except for several short-term declines. The gold price increased by a factor of approximately 5.5 over the last 10 years, while the S&P 500 index fluctuated in the range from approximately 670 points to approximately 1570 points.

The gold price fluctuates in the range of \$250–\$420 during the 1990s but exhibits a sharply increasing trend after 2002. In the 1970s and early 1980s, the United States and European countries suffered from high inflation, unemployment and low growth, which were mainly attributable to an oil crisis caused by the Organization of the Petroleum Exporting Countries (OPEC). These factors contributed to the bull market of gold. In contrast to the 1970s, for approximately two decades beginning in the early 1980s, the gold market shifted to a bear market. Most of this period corresponds to the 'great moderation', when the US economy achieved low inflation and stable growth. In the late 1990s in particular, the stock prices of Information Technology (IT)-related companies continued to rise, and the appeal of equity investment rose. The collapse of the IT bubble and the terrorist attacks on 11 September 2001, marked the opening of the bull gold market again. In the 2000s, the demand for gold for jewellery and industrial use expanded owing to the emergence of China and India. Furthermore, the increasing number of participants

[4] For the application of the CCF approach, refer to, for example, Bhar and Hamori (2005, 2008), Inagaki (2007), Hoshikawa (2008) and Tamakoshi (2011). Caporale *et al*. (2002) adopt a Vector Autoregressive (VAR) multivariate GARCH framework and causality test for relevant zero restrictions on the conditional variance parameter. Furthermore, this test can test for *s* structural break in the volatility.
[5] The determination process of gold fixing is described briefly by Capie *et al*. (2005) and Lucey and Tully (2006).
[6] Refer to http://www.lbma.org.uk/pages/index.cfm.
[7] Refer to http://www.stlouisfed.org/.

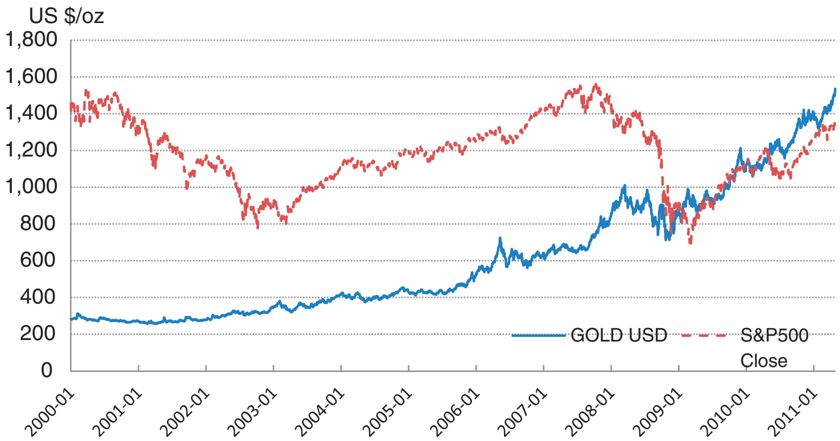

Fig. 1. Gold price and S&P 500 index: from 4 January 2000 to 28 April 2011
Source: Gold price data comes from the London Bullion Market Association (LBMA) homepage. The S&P 500 index data comes from the Federal Reserve Bank of St. Louis homepage.

in the gold market, because of the market's easy access for general investors owing to the introduction of gold-linked ETFs, spurred the rising gold price. After the financial crisis in 2008, the fear of high inflation in emerging economies such as the BRIC countries and monetary expansion in advanced countries has accelerated the sharp rise in the price of gold. In 2011, many central banks (i.e. those of Mexico, Russia, Bolivia and Thailand) increased the gold reserves. Furthermore, general investors in Asian countries (China, India, Vietnam, Indonesia and Thailand) and European countries (France, Germany and Switzerland) actively continue to purchase gold because of the speculation opportunity and the sovereign debt crisis (World Gold Council, 2011). Figure 2(a) and (b) display, respectively, the evolution of the gold price and the S&P 500 index returns in our sample period.

Descriptive statistics

Table 1 reports the descriptive statistics of the returns on gold and on the S&P 500 index. For both data series, the natural logarithms are taken, and each return series is calculated as follows: $r_t = \{\ln(y_t) - \ln(y_{t-1})\} \times 100$, where y_t is the gold price or the S&P 500 index. As illustrated in Fig. 1, gold price was almost monotonically increasing except for some short-term declines during the sample period; consequently, the mean gold return is positive (0.060). While the mean S&P 500 index return is negative (−0.002), it is essentially zero and more volatile than the gold market (the SD is 1.157 for the gold return and 1.369 for the S&P 500 index return). In this sense, gold is a more efficient asset relative to stocks during this period. Kurtosis exhibits a leptokurtic distribution, and as clearly shown by the Jarque–Bera test statistic and its p-value, the series of both the gold return and the S&P 500 index return are not normal at the 1% significance level. The correlation coefficient (−0.052) shows an almost zero or a slightly negative relationship between both return series during this sample period.

IV. Method: Hong's Approach

In this section, we briefly summarize the procedure to test the causality in mean and the causality in variance developed by Hong (2001). As previously mentioned, we employ Hong's test based on the CCF approach developed by Cheung and Ng (1996) to examine the causality between the gold return and the S&P 500 index return. Hong (2001) proposes incorporating the nonuniform weighting cross-correlations into the CCF approach to modify the size distortion of the test statistic generated when the causality in mean exists. Hong's test statistic is applied to test the causality in mean and variance between two stationary variables of interest.

Basic concept

Suppose that there are two stationary time series, X_t and Y_t. We define the following three information sets:

$$I_{1t} = (X_{t-j}; j \geq 0) \qquad (1)$$

$$I_{2t} = (Y_{t-j}; j \geq 0) \qquad (2)$$

$$I_t = \left(X_{t-j}, Y_{t-j}; j \geq 0\right) \qquad (3)$$

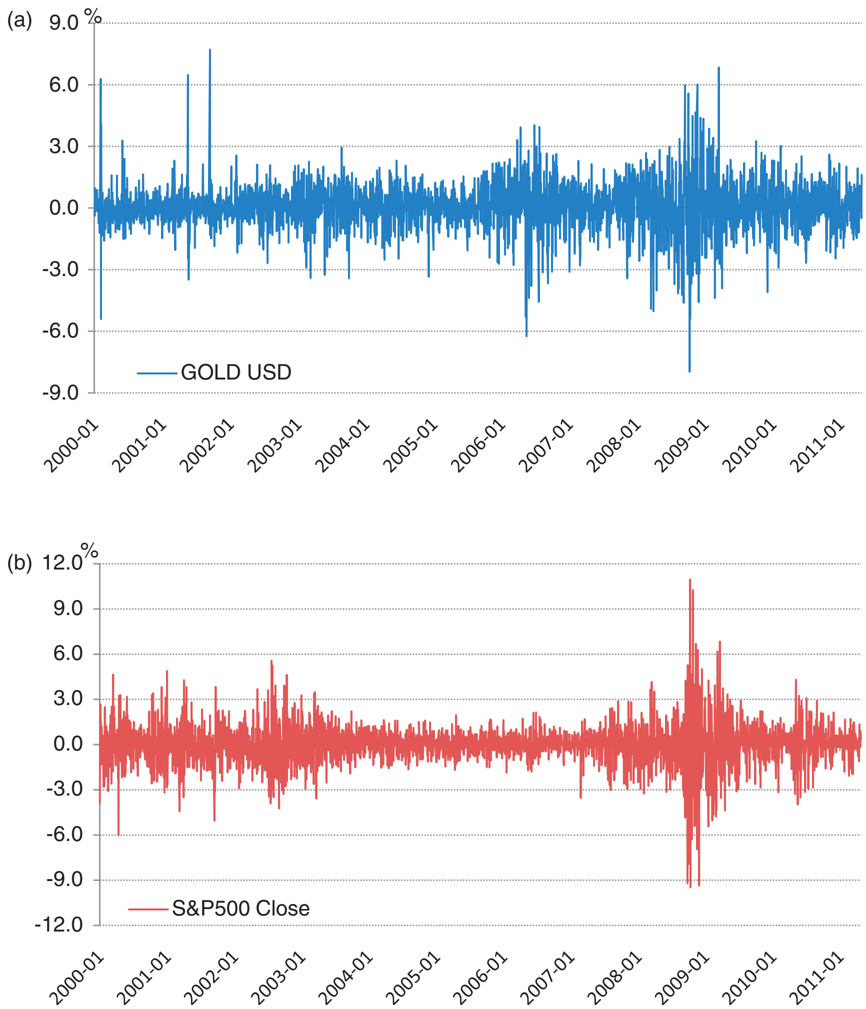

Fig. 2. (a) Gold return: from 4 January 2000 to 28 April 2011; (b) S&P500 index return: from 4 January 2000 to 28 April 2011

Table 1. Descriptive statistics: full sample period

	Return on gold (%)	Return on the S&P 500 index (%)
Mean	0.060	−0.002
Median	0.057	0.055
SD	1.157	1.369
Maximum	7.706	10.957
Minimum	−7.972	−9.470
Skewness	−0.065	−0.118
Kurtosis	8.148	10.567
JB	3130.287	6765.906
p-value	0.000	0.000
Correlation coefficient	−0.052	

Notes: JB is the Jarque–Bera test statistic. *p*-value is the probability value of the Jarque–Bera test statistic.

Then, if

$$E[X_t|I_{1,t-1}] \neq E[X_t|I_{t-1}] \tag{4}$$

we say that Y_t causes X_t in mean. Similarly, if

$$E[Y_t|I_{2,t-1}] \neq E[Y_t|I_{t-1}] \tag{5}$$

we say that X_t causes Y_t in mean.

A similar definition is applied to variance. If

$$E[(X_t - \mu_{x,t})^2|I_{1,t-1}] \neq E[(X_t - \mu_{x,t})^2|I_{t-1}] \tag{6}$$

then Y_t causes X_t in variance, where $\mu_{x,t}$ is the mean of X_t conditioned on $I_{1,t-1}$. Similarly, if

$$E[(Y_t - \mu_{y,t})^2|I_{2,t-1}] \neq E[(Y_t - \mu_{y,t})^2|I_{t-1}] \tag{7}$$

then X_t causes Y_t in variance, where $\mu_{y,t}$ is the mean of Y_t conditioned on $I_{2,t-1}$.

Two-step procedure

In the first step, we estimate a set of univariate time series models (e.g. the AR-GARCH model) that allow for time variation in both the conditional mean and conditional variance. In the second step, we construct the residuals standardized by the conditional mean and the squared residuals standardized by the conditional variance.

The CCF of the standardized residuals is used to test the null hypothesis of no causality in mean. The CCF of the squared standardized residuals is used to test the null hypothesis of no causality in variance.

Suppose that X_t and Y_t are written as

$$X_t = \mu_{x,t} + \sqrt{h_{x,t}}\varepsilon_t \tag{8}$$

and

$$Y_t = \mu_{y,t} + \sqrt{h_{y,t}}\zeta_t \tag{9}$$

where ε_t and ζ_t are two independent white noise processes with zero mean and unit variance.

For the causality in mean test, the following standardized innovations are used:

$$\varepsilon_t = \frac{X_t - \mu_{x,t}}{\sqrt{h_{x,t}}} \tag{10}$$

$$\zeta_t = \frac{Y_t - \mu_{y,t}}{\sqrt{h_{y,t}}} \tag{11}$$

Because both ε_t and ζ_t are unobservable, their estimates, $\hat{\varepsilon}_t$ and $\hat{\zeta}_t$, are used to test the null hypothesis of no causality in mean.

Next, we calculate the sample cross-correlation coefficient at lag k, $\hat{r}_{\epsilon\zeta}(k)$:

$$\hat{r}_{\epsilon\zeta}(k) = \frac{c_{\varepsilon\zeta}(k)}{\sqrt{c_{\varepsilon\varepsilon}(0)c_{\zeta\zeta}(0)}} \tag{12}$$

where $c_{\varepsilon\zeta}(k)$ is the k-th lag sample cross-covariance given by

$$c_{\varepsilon\zeta}(k) = \begin{cases} \frac{1}{T}\sum_{t=1}^{T-k}\left(\hat{\varepsilon}_t - \overline{\hat{\varepsilon}}\right)\left(\hat{\zeta}_{t+k} - \overline{\hat{\zeta}}\right) & \text{for } k = 0, 1, 2, \ldots \\ \frac{1}{T}\sum_{t=1}^{T-k}\left(\hat{\varepsilon}_{t-k} - \overline{\hat{\varepsilon}}\right)\left(\hat{\zeta}_t - \overline{\hat{\zeta}}\right) & \text{for } k = 0, -1, -2, \ldots \end{cases} \tag{13}$$

and $c_{\varepsilon\varepsilon}(0)$ and $c_{\zeta\zeta}(0)$ are defined as the sample variances of ε_t and ζ_t, respectively.

Under the regularity condition, the following condition holds:

$$S_1 = T\sum_{i=1}^{k}\hat{r}^2_{\varepsilon\zeta}(i) \xrightarrow{L} \chi^2(k) \tag{14}$$

where $\chi^2(k)$ indicates a chi-square distribution with k degrees of freedom. We can use this test statistic to test the null hypothesis of no causality in mean from lag 1 to lag k. To test for causality in mean from lag 1 to lag k, we compare S_1 with the chi-square distribution. If the test statistic is larger than the critical value of the chi-square distribution, then we reject the null hypothesis.

For the causality in variance test, let u_t and v_t be the squares of the standardized innovations, given by

$$u_t = \frac{(X_t - \mu_{x,t})^2}{h_{x,t}} = \varepsilon_t^2 \tag{15}$$

and

$$v_t = \frac{(Y_t - \mu_{y,t})^2}{h_{y,t}} = \zeta_t^2 \tag{16}$$

Because both u_t and v_t are unobservable, their estimates, $\hat{u}_t$ and $\hat{v}_t$, are used to test the null hypothesis of no causality in variance.

Next, we calculate the sample cross-correlation coefficient at lag k, $\hat{r}_{uv}(k)$

$$\hat{r}_{uv}(k) = \frac{c_{uv}(k)}{\sqrt{c_{uu}(0)c_{vv}(0)}} \tag{17}$$

where $c_{uv}(k)$ is the k-th lag sample cross-covariance given by

$$c_{uv}(k) = \begin{cases} \frac{1}{T}\sum_{t=1}^{T-k}\left(\hat{u}_t - \overline{\hat{u}}\right)\left(\hat{v}_{t+k} - \overline{\hat{v}}\right) & \text{for } k = 0, 1, 2, \ldots \\ \frac{1}{T}\sum_{t=1}^{T-k}\left(\hat{u}_{t-k} - \overline{\hat{u}}\right)\left(\hat{v}_t - \overline{\hat{v}}\right) & \text{for } k = 0, -1, -2, \ldots \end{cases} \tag{18}$$

and $c_{uu}(0)$ and $c_{vv}(0)$ are defined as the sample variances of u_t and v_t, respectively.

Under the regularity condition, the following condition holds:

$$S_2 = T\sum_{i=1}^{k}\hat{r}^2_{uv}(i) \xrightarrow{L} \chi^2(k) \tag{19}$$

We can use this test statistic to test the null hypothesis of no causality in variance from lag 1 to lag k. To test for causality in variance from lag 1 to lag k, we compare S_2 with the chi-square distribution. If the test statistic is larger than the critical value of the chi-square distribution, then we reject the null hypothesis.

As discussed above, we can use S_1 and S_2 to test the causality in mean and variance, respectively. However, these test statistics can be subject to severe size distortions in the presence of causality in mean. To overcome this limitation, Hong (2001) proposes incorporating the nonuniform weighting cross-correlations into the CCF approach. The modified test statistics are as follows:

$$M_1 = \frac{S_1 - k}{\sqrt{2k}} \xrightarrow{L} N(0,1) \tag{20}$$

and

$$M_2 = \frac{S_2 - k}{\sqrt{2k}} \xrightarrow{L} N(0,1) \tag{21}$$

We use upper-tailed $N(0,1)$ critical values because these test statistics are one-sided tests. If the test statistic is larger than the critical value of the standard normal distribution, we reject the null hypothesis of no causality in mean or no causality in variance.

V. Empirical Results

In this section, we demonstrate whether there exist causality in mean and causality in variance between gold and the S&P 500 index results using Hong's approach. We first show the empirical results for the full sample period. Then, we provide the empirical results for two subsample periods: from 4 January 2000 to 8 August 2007 and from 9 August 2007 to 28 April 2011. This sample decomposition seems reasonable because the subprime mortgage problem first gained the notice of market participants around the summer of 2007. In addition, to check the robustness of the results, we apply the causality test to different subsample periods. In the following discussion, for convenience, we use 'performance' and 'uncertainty' to refer to the mean and variance, respectively, in the context of causality.

Full sample period

First, we report the empirical results for the full sample period: from 4 January 2000 to 28 April 2011. As a preliminary analysis, although not reported in detail, we implement the Augmented Dickey–Fuller (ADF) unit root test and reject the null hypothesis of a unit root for both return series for all sample periods, including the subsamples analysed later.[8]

In the first step, we estimate a set of AR(k)-EGARCH(p,q) processes with a generalized error distribution for both return series[9]:

$$y_t = a_0 + \sum_{i=1}^{k} a_i y_{t-i} + \varepsilon_t, \varepsilon_t = \sigma_t z_t, z_t \sim GED(\kappa) \tag{22}$$

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p}\left(\alpha_i\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right) + \sum_{i=1}^{q}\beta_i \ln(\sigma_{t-i}^2) \tag{23}$$

where y_t denotes the gold return or the S&P 500 index return, ε_t is the error term with heteroscedasticity, Ω_{t-1} is information set at time $t-1$, κ is a positive parameter measuring the skewness of the distribution, and σ_t^2 denotes the conditional variance of ε_t, i.e., $E(\varepsilon_t^2|\Omega_{t-1}) = \sigma_t^2$. That is, Equations 22 and 23 represent the mean and variance equations for both variables, respectively. The EGARCH model can capture the so-called leverage effects (also known as asymmetric effects). In Equation 23, α_i and γ_i capture the size effect and the sign effect, respectively. In the EGARCH(1,1) model, for example, if $\varepsilon_{t-1}/\sigma_{t-1}$ is negative, the effect on conditional volatility is $\alpha_1 - \gamma_1$. Conversely, if $\varepsilon_{t-1}/\sigma_{t-1}$ is positive, the effect on conditional volatility is $\alpha_1 + \gamma_1$. We set the maximum lag order in the AR part to 10 and consider (1,1), (1,2), (2,1) and (2,2) as specifications for the EGARCH part in the choice of the model. From among these specifications, we select the final model based on the Akaike Information Criterion (AIC) and the diagnostic test for autocorrelation of residuals.

Table 2 reports the estimation results of the AR-EGARCH model for the gold return and the S&P 500 index return. The selected model is AR(9)-EGARCH(1,1) for the gold return and AR(4)-EGARCH(2,1) for the S&P 500 index return. For the gold return, the coefficient of the ARCH term is 0.097, the leverage term is 0.041, the GARCH term is 0.992 and all parameters for the variance equation are statistically significant at the 1% level. For the S&P 500 index return, the coefficients of the ARCH terms are −0.208 and 0.330, the leverage terms are −0.253 and 0.138 and the GARCH term is 0.984, and all parameters for the variance equation are statistically significant at the 1% level. While $Q(20)$ in the gold return equation shows that the autocorrelation of standardized residuals remains weak (i.e. 10% significance level), the overall model specification of both

[8] The details of the unit root test are available upon request.
[9] For the ARCH model and its extension including the EGARCH model, refer to Bollerslev *et al.* (1992, 1994), Hamilton (1994) and Enders (2010). For the details of the EGARCH model, refer to Nelson (1991).

Table 2. Estimation results of the AR-EGARCH model: full sample period

$$\text{Estimated equations: } y_t = a_0 + \sum_{i=1}^{k} a_i y_{t-i} + \varepsilon_t, \quad \varepsilon_t = \sigma_t z_t, \quad z_t \sim GED(k)$$

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p}\left(\alpha_i\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \gamma_i\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right) + \sum_{i=1}^{q}\beta_i\ln(\sigma_{t-i}^2)$$

	Gold		S&P 500 index	
Parameter	Estimate	SE	Estimate	SE
a_0	0.060***	0.015	0.044***	0.016
a_1	−0.032*	0.017	−0.069***	0.016
a_2	0.022	0.017	−0.045**	0.018
a_3	−0.008	0.017	0.006	0.018
a_4	0.011	0.017	0.010	0.017
a_5	−0.002	0.017		
a_6	−0.039	0.017		
a_7	−0.009	0.017		
a_8	0.000	0.016		
a_9	0.029*	0.016		
ω	−0.071***	0.010	−0.097***	0.013
α_1	0.097***	0.014	−0.208***	0.045
α_2			0.330***	0.047
γ_1	0.041***	0.010	−0.253***	0.030
γ_2			0.138***	0.031
β_1	0.992***	0.003	0.984***	0.003
Log-likelihood	−3997.091		−4111.811	
$Q(20)$	28.610		17.857	
p-value	0.096		0.597	
$Q^2(20)$	9.227		17.586	
p-value	0.980		0.615	

Notes: This table reports the AR-EGARCH estimation results based on Equations 22 and 23 for gold and the S&P 500 index returns. $Q(20)$ and $Q^2(20)$ denote the Ljung–Box test statistic for no autocorrelation of standardized residuals and squared standardized residuals up to 20 lags, respectively.
*, ** and *** indicate statistical significance at the 10, 5 and 1% levels, respectively.

series is adequate. Figure 3 plots the estimated volatilities of the gold price and the S&P 500 index returns.

Next, we construct the standardized residuals and squared standardized residuals for the cross-correlation analysis based on Hong (2001). The empirical results of the nonuniform weighting cross-correlation analysis for the entire sample period are given in Table 3. This result shows that there exists statistically significant causality in mean from the S&P 500 index to gold at lags 5, 10 and 15, that all statistics are statistically significant at the 1% level and that there is no causality in mean from gold to the S&P 500 index. Hence, in this sample period, we can conclude that there exists a unidirectional causality in mean from the S&P 500 index return to the gold return. On the other hand, for causality in variance, there is no evidence of causality from the S&P 500 index to gold and vice versa. This finding suggests that there exists no volatility transmission between the gold market and the stock market during this sample period.

One reason for the existence of a unidirectional causality in mean from the S&P 500 index to gold is that gold price has been persistently increasing regardless of the stock market fluctuations over the sample period (see Fig. 1). The lack of causality in variance implies that there is no volatility transmission between the two markets. The result that there is no causality in variance from gold to the S&P 500 index shows that gold is not effective as a leading indicator of uncertainty in the stock market. Furthermore, as stated below, if we consider that causality in variance from the S&P 500 index to gold has occurred because of flight-to-quality, we can infer that gold is not considered a hedge or a safe haven for stocks in the long-run.

Subsample period

In this subsection, we report the empirical results for the subsample periods. To focus on the change in the role of gold, let us decompose the entire sample into

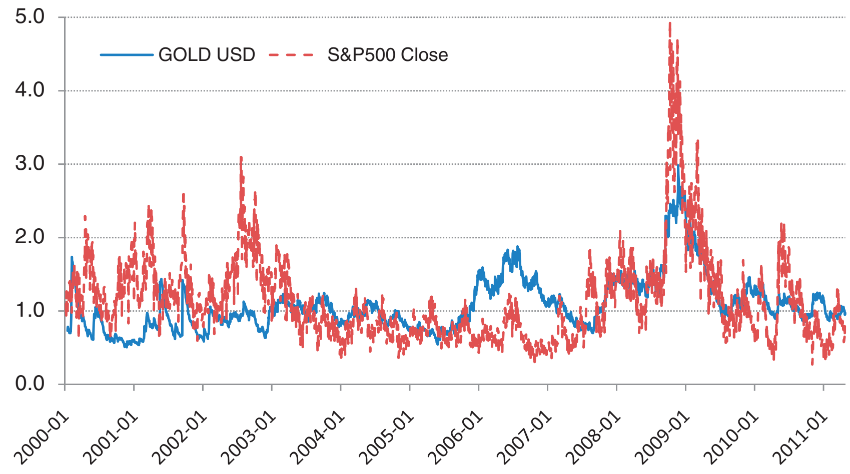

Fig. 3. The volatilities of gold price and S&P500 index: from 4 January 2000 to 28 April 2011

Table 3. Test statistics for causality in mean and variance: full sample period

	k	5	10	15
From gold to S&P 500 index	M_1	0.597	−0.192	−0.507
	M_2	−1.123	−1.643	−2.057
From S&P 500 index to gold	M_1	3.696***	2.486***	2.519***
	M_2	0.778	0.321	−0.533

Notes: This table shows the causality test statistic calculated from Equations 20 and 21. k indicates a truncated lag number. M_1 and M_2 denote the test statistics for causality in mean and variance, respectively. If the test statistic is larger than the critical value of the standard normal distribution, the null hypothesis of no causality is rejected. *** Indicates statistical significance at the 1% level.

two periods. The first sample period is from 4 January 2000 to 8 August 2007, and the second is from 9 August 2007 to 28 April 2011. The motivation for this sample decomposition is that BNP Paribas, a major French bank, froze three of its funds related to subprime mortgage securities because it was impossible to evaluate their Net Asset Values (NAVs). It is widely recognized that this incident triggered the outbreak of the subprime mortgage crisis. In the next subsection, we demonstrate whether the results from this division of the sample period are robust to other possible sample period decompositions.

From 2000 to the actualization of the subprime mortgage problem

Table 4 reports the estimation results of the AR-EGARCH model for both return series for the first sample period. The selected model is AR(1)-EGARCH(2,1) for gold return and AR(7)-EGARCH(2,2) for the S&P 500 index return. For the gold return, the coefficient of the ARCH term is 0.235, the leverage term is −0.008, the GARCH term is 0.987 and all parameters for the variance equation are statistically significant at the 1% level except for γ_1. For the S&P 500 index return, the coefficients of the ARCH terms are −0.144 and 0.194, the leverage terms are −0.266 and 0.220, the GARCH terms are 1.466 and −0.472 and all parameters for the variance equation are statistically significant at the 1% level. $Q(20)$ and $Q^2(20)$ and its p-value indicate that no autocorrelation remains; thus, both estimated models are fitted fairly well.

The empirical results of the nonuniform weighting cross-correlation analysis for the first sample period are given in Table 5. The results are qualitatively similar to those for the full sample period given in Table 3, but in this case, there obviously exists a feedback effect on causality in mean. In particular, not only is causality in mean remarkable in low-order lags but also the S&P 500 index performance significantly causes the gold return in high-order lags. Thus, gold can be seen as an effective leading indicator of stock market performance in the short-run (i.e. approximately a week ahead). For causality in variance, there is no evidence of causality. According to this result, much like that for the full sample period, we can infer that neither does gold play a role as a leading indicator of stock market uncertainty nor can it be regarded as a hedge or a safe haven for stocks during this sample period.

From the actualization of the subprime mortgage problem to present

Table 6 reports the estimation results of the AR-EGARCH model for both returns, gold and the

Table 4. Estimation results of the AR-EGARCH model: first sample period

$$\text{Estimated equations: } y_t = a_0 + \sum_{i=1}^{k} a_i y_{t-i} + \varepsilon_t, \quad \varepsilon_t = \sigma_t z_t, \quad z_t \sim GED(k)$$

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \left(\alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right) + \sum_{i=1}^{q} \beta_i \ln(\sigma_{t-i}^2)$$

	Gold		S&P 500 index	
Parameter	Estimate	SE	Estimate	SE
a_0	0.042***	0.016	0.030	0.019
a_1	−0.021	0.352	−0.057***	0.021
a_2			−0.043**	0.021
a_3			0.005	0.022
a_4			−0.003	0.021
a_5			−0.024	0.021
a_6			−0.034	0.022
a_7			−0.047**	0.022
ω	−0.057***	0.014	−0.042***	0.011
α_1	0.235***	0.048	−0.144***	0.048
α_2	−0.161***	0.049	0.194***	0.054
γ_1	−0.008	0.036	−0.236***	0.034
γ_2	0.070*	0.036	0.220***	0.028
β_1	0.987***	0.005	1.466***	0.119
β_2			−0.472***	0.118
Log-likelihood	−2462.135		−2518.796	
$Q(20)$	27.352		9.756	
p-value	0.126		0.972	
$Q^2(20)$	11.155		16.176	
p-value	0.942		0.706	

Notes: This table reports the AR-EGARCH estimation results based on Equations 22 and 23 for gold and the S&P 500 index returns. $Q(20)$ and $Q^2(20)$ denote the Ljung–Box test statistic for no autocorrelation of standardized residuals and squared standardized residuals up to 20 lags, respectively.
*, ** and *** indicate statistical significance at the 10, 5 and 1% levels, respectively.

Table 5. Test statistics for causality in mean and variance: first sample period

	k	5	10	15
From gold to S&P 500 index	M_1	2.641***	1.221	0.711
	M_2	−1.079	−1.441	−1.715
From S&P 500 index to gold	M_1	3.687***	1.780**	2.154**
	M_2	−0.139	−1.047	−1.579

Notes: This table shows the causality test statistic calculated from Equations 20 and 21. k indicates a truncated lag number. M_1 and M_2 denote the test statistics for causality in mean and variance, respectively. If the test statistic is larger than the critical value of the standard normal distribution, the null hypothesis of no causality is rejected. ** and *** indicate statistical significance at the 5 and 1% levels, respectively.

S&P 500 index. The selected model is AR(1)-EGARCH(2,1) for the gold return and AR(3)-EGARCH(2,2) for the S&P 500 index return. For the gold return, the coefficients of the ARCH terms are −0.311 and 0.457, the leverage terms are −0.135 and 0.165, the GARCH term is 0.994 and all parameters for the variance equation are statistically significant at the 1% level. For the S&P 500 index return, the coefficients of the ARCH terms are −0.250 and 0.386, the leverage terms are −0.228 and 0.133, the GARCH terms are 1.327 and −0.348 and all parameters for the variance equation are statistically significant at the conventional levels. $Q(20)$ and $Q^2(20)$ and its p-value indicate that both estimated models are fitted fairly well.

The empirical results of the nonuniform weighting cross-correlation analysis for the second sample period are given in Table 7. The results differ from those for the first sample period given in Table 5. As seen in Table 7, causality in mean from gold to the S&P 500 index vanishes, and there exists only a unidirectional causality in mean from the S&P 500 index to gold at all truncated lags. Similarly, it appears that there is no causality in variance from gold to the S&P 500 index, but evidently, there exists a unidirectional causality in variance from the S&P

Table 6. Estimation results of the AR-EGARCH model: second sample period

$$\text{Estimated equations: } y_t = a_0 + \sum_{i=1}^{k} a_i y_{t-i} + \varepsilon_t, \quad \varepsilon_t = \sigma_t z_t, \quad z_t \sim GED(k)$$

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \left(\alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right) + \sum_{i=1}^{q} \beta_i \ln(\sigma_{t-i}^2)$$

	Gold		S&P 500 index	
Parameter	Estimate	SE	Estimate	SE
a_0	0.130***	0.034	0.082**	0.034
a_1	−0.026	0.026	−0.083***	0.026
a_2			−0.040	0.029
a_3			0.008	0.030
ω	−0.109***	0.022	−0.098***	0.028
α_1	−0.311***	0.074	−0.250***	0.088
α_2	0.457***	0.077	0.386***	0.109
γ_1	−0.135***	0.047	−0.228***	0.058
γ_2	0.165***	0.045	0.133**	0.057
β_1	0.994***	0.006	1.327***	0.186
β_2			−0.348*	0.181
Log-likelihood	−1519.088		−1565.343	
$Q(20)$	23.916		11.166	
p-value	0.246		0.942	
$Q^2(20)$	26.435		14.214	
p-value	0.152		0.819	

Notes: This table reports the AR-EGARCH estimation results based on Equations 22 and 23 for gold and the S&P 500 index returns. $Q(20)$ and $Q^2(20)$ denote the Ljung–Box test statistic for no autocorrelation of standardized residuals and squared standardized residuals up to 20 lags, respectively.
*, ** and *** indicate statistical significance at the 10, 5 and 1% levels, respectively.

Table 7. Test statistics for causality in mean and variance: second sample period

	k	5	10	15
From gold to S&P 500 index	M_1	−0.853	0.531	−0.102
	M_2	0.714	−0.139	−0.643
From S&P 500 index to gold	M_1	1.622*	2.002**	2.147**
	M_2	1.743**	5.275***	5.374***

Notes: This table shows the causality test statistic calculated from Equations 20 and 21. k indicates a truncated lag number. M_1 and M_2 denote the test statistics for causality in mean and variance, respectively. If the test statistic is larger than the critical value of the standard normal distribution, the null hypothesis of no causality is rejected. *, ** and *** indicate statistical significance the 10, 5 and 1% levels, respectively.

500 index to gold at all three lags. This result is crucial for our objective because it implies that the relationship between gold return volatility and stock market uncertainty changed during the recent financial turmoil.

A natural question then arises as to why does causality in mean from gold to the S&P 500 index disappears and why causality in variance from the S&P 500 index to gold appears. The one convincing hypothesis is that investors are driven according to the so-called flight-to-quality by fear of financial losses, and hence, they rush to purchase gold assets directly or to indirectly invest in gold as a hedge or a safe haven. Therefore, it seems that a unilateral causality from the S&P 500 index to gold has been observed in the current financial crisis. Accordingly, gold is not always regarded as a hedge or a safe haven for stocks, but gold is demanded as a refuge in abnormal situations such as the recent financial crisis. This hypothesis empirically supports the popular opinion of flight-to-quality, and it is partly consistent with the findings of Baur and Lucey (2010) and Baur and McDermott (2010) in the debate over gold as a hedge or a safe haven.

Robustness check

Finally, to check the robustness of our results, we conduct the same testing procedure for different subsample periods, before and after Lehman Brothers' bankruptcy, specifically from 4 January 2000 to 12 September 2008 and from 15 September 2008 to 28 April 2011. This division of the sample corresponds to when a symbolic event embodying the current financial crisis occurred.

Although the details are omitted, the results are summarized as follows[10]: (1) causality in mean and variance are qualitatively similar to those obtained earlier and (2) causality in mean is qualitatively similar to that obtained earlier, while a unilateral causality in variance from the S&P 500 index to gold is detected again at lags 10 and 15 for the second sample period. Accordingly, we can conclude that the empirical results obtained previously are robust to sample divisions according to the outbreak of the current financial crisis.

VI. Concluding Remarks

This article investigates the causal relationships between the gold return and stock market performance or uncertainty using nonuniform weighting cross-correlations developed by Hong (2001). Using the daily data covering the period from January 2000 to April 2011, causality in mean and variance between the gold return and the S&P 500 index return is examined. Furthermore, we divide the sample into two subsample periods to focus on the change of the role of gold as an alternative investment asset. The main findings are summarized as follows:

(1) There exists a unidirectional causality in mean from the S&P 500 index to gold, but no causality in variance is detected from gold to the S&P 500 index and vice versa for the full sample period. Thus, there is no volatility transmission between both markets in the long-run.
(2) For the first sample period (before the actualization of the subprime mortgage problem), we detect bidirectional causality in mean, though there exists no causality in variance from the S&P 500 index to gold and vice versa.
(3) For the second sample period (after the actualization of the subprime mortgage problem), there exists not just a unilateral causality in mean but also a unilateral causality in variance from the S&P 500 index to gold.
(4) For different subsample periods (before and after Lehman Brothers' bankruptcy), we obtain qualitatively similar results. Consequently, we can conclude that the results obtained from our analysis are robust to the choice of the beginning of the current financial crisis.

In all sample periods examined here, causality in mean from the S&P 500 index to gold commonly exists. It appears that this causation is, in part, as seen in Fig. 1, due to the persistent increases in the gold price regardless of the stock market behaviour during the sample period.

The last of our findings is crucial to understanding the role of gold, which is our main purpose in this article, because it implies that the relationship between gold and stock market uncertainty has changed during the recent financial turmoil. As for the underlying reason, we hypothesize that investors are driven to flight-to-quality by fear of financial collapse, and consequently, rush into purchasing gold-linked assets, such as ETFs, as a hedge or a safe haven. This hypothesis supports the common view of flight-to-quality with empirical evidence and is partly supported by the findings of some previous works, especially with respect to the suggestion that gold does not always act as a hedge or a safe haven for stocks, as argued by Baur and Lucey (2010). This hypothesis, however, does not necessarily imply that gold effectively reduces losses in a falling stock market.

For future research, as suggested in some previous works, exchange rate fluctuations, especially the depreciation of the dollar, should be taken into account to determine gold return volatility. Furthermore, inflation, which is associated with dollar depreciation, is expected to result in the demand for gold as a hedge. The presence of these factors and other possible determinants that simultaneously influence gold demand requires us to specify a multivariate system (e.g. multivariate GARCH model) to capture the dynamic linkages among them. In addition, this article examines the causality only from the perspective of the agents holding assets in US dollars. It is ambiguous whether our findings apply to agents holding assets in different currencies. Thus, we should compare our findings with other results using various currencies. We leave these issues for future research.

References

Aggarwal, R. and Lucey, B. (2007) Psychological barriers in gold prices?, *Review of Financial Economics*, **16**, 217–30.

[10] The details of the empirical results are available upon request.

Baur, D. and Lucey, B. (2010) Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold, *The Financial Review*, **45**, 217–29.

Baur, D. and McDermott, T. (2010) Is gold a safe haven? International evidence, *Journal of Banking and Finance*, **34**, 1886–98.

Bhar, R. and Hamori, S. (2004) Information flow between price change and trading volume in gold futures contracts, *International Journal of Business and Economics*, **3**, 45–56.

Bhar, R. and Hamori, S. (2005) Causality in variance and the type of traders in crude oil futures, *Energy Economics*, **27**, 527–39.

Bhar, R. and Hamori, S. (2008) Information content of commodity futures prices for monetary policy, *Economic Modelling*, **25**, 274–83.

Bollerslev, T., Chou, R. and Kroner, K. (1992) ARCH modeling in finance: a review of theory and empirical evidence, *Journal of Econometrics*, **52**, 5–59.

Bollerslev, T., Engle, R. and Nelson, D. (Eds) (1994) ARCH models, in *Handbook of Econometrics*, Vol. 4, North-Holland, Amsterdam, pp. 2959–3038.

Capie, F., Mills, T. and Wood, G. (2005) Gold as a hedge against the dollar, *Journal of International Financial Markets, Institutions and Money*, **15**, 343–52.

Caporale, G. M., Pittis, N. and Spagnolo, N. (2002) Testing for causality-in-variance: an application to the East Asian markets, *International Journal of Finance and Economics*, **7**, 235–45.

Chan, K. F., Treepongkaruna, S., Brooks, R. and Gray, S. (2011) Asset market linkages: evidence from financial, commodity and real estate assets, *Journal of Banking and Finance*, **35**, 1415–26.

Cheung, Y. W. and Ng, L. (1996) A causality in variance test and its application to financial market prices, *Journal of Econometrics*, **72**, 33–48.

Ciner, C., Gurdgiev, C. and Lucey, B. (2010) Hedges and safe havens – an examination of stocks, bonds, oil, gold and dollar, Discussion paper No. 337, Institute for International Integration Studies.

Cohen, G. and Qadan, M. (2010) Is gold still a shelter to fear?, *American Journal of Social and Management Sciences*, **1**, 39–43.

Diebold, F. and Yilmaz, K. (2009) Measuring financial asset return and volatility spillovers, with application to global equity markets, *The Economic Journal*, **119**, 158–71.

Diebold, F. and Yilmaz, K. (Eds) (2010) Equity market spillovers in the Americas, in *Financial Stability, Monetary Policy, and Central Banking*, Vol. 15, Central Bank of Chile, Santiago, Chile, pp. 199–214.

Do, G., McAleer, M. and Sribonchitta, S. (2009) Effects of international gold market on stock exchange volatility: evidence from ASEAN emerging stock markets, *Economics Bulletin*, **29**, 599–610.

Economist (2009) *Haring Away,* 26 February 2009, The Economist Newspaper Limited, London.

Economist (2010) *Store of Value,* 8 July 2010, The Economist Newspaper Limited, London.

Enders, W. (2010) *Applied Econometric Time Series*, 3rd edn, John Wiley & Sons, Inc., Hoboken, NJ.

Hamilton, J. (1994) *Time Series Analysis*, Princeton University Press, Princeton.

Hillier, D., Draper, P. and Faff, R. (2006) Do precious metals shine? An investment perspective, *Financial Analysts Journal*, **62**, 98–106.

Hong, Y. (2001) A test for volatility spillover with application to exchange rates, *Journal of Econometrics*, **103**, 183–224.

Hoshikawa, T. (2008) The causal relationships between foreign exchange intervention and exchange rate, *Applied Economics Letters*, **15**, 519–22.

Inagaki, K. (2007) Testing for volatility spillover between the British pound and the euro, *Research in International Business and Finance*, **21**, 161–74.

Joy, M. (2011) Gold and the US dollar: hedge or haven?, *Finance Research Letters*, **8**, 120–31.

Kim, M. and Dilts, D. (2011) The relationship of the value of the dollar, and the prices of gold and oil: a tale of asset risk, *Economics Bulletin*, **31**, 1151–62.

Lawrence, C. (2003) *Why is Gold Different from Other Assets? An empirical Investigation*, World Gold Council, London.

Lucey, B. and Tully, E. (2006) Seasonality, risk and return in daily COMEX gold and silver data 1982–2002, *Applied Financial Economics*, **16**, 319–33.

Mahdavi, S. and Zhou, S. (1997) Gold and commodity prices as leading indicators of inflation: tests of long-run relationship and predictive performance, *Journal of Economics and Business*, **49**, 475–89.

Nelson, D. (1991) Conditional heteroskedasticity in asset returns: a new approach, *Econometrica*, **59**, 349–70.

Pukthuanthong, K. and Roll, R. (2011) Gold and the dollar (and the euro, pound, and yen), *Journal of Banking and Finance*, **35**, 2070–83.

Sari, R., Soytas, U. and Hacihasanoglu, E. (2011) Do global risk perceptions influence world oil prices?, *Energy Economics*, **33**, 515–24.

Smith, G. (2002) Tests of the random walk hypothesis for London gold prices, *Applied Economics Letters*, **9**, 671–4.

Sumner, S., Johnson, R. and Soenen, L. (2010) Spillover effects among gold, stocks, and bonds, *Journal of CENTRUM Cathedra*, **3**, 106–20.

Tamakoshi, G. (2011) European sovereign debt crisis and linkage of long-term government bond yields, *Economics Bulletin*, **31**, 2191–203.

Tully, E. and Lucey, B. (2007) A power GARCH examination of the gold market, *Research in International Business and Economics*, **21**, 316–25.

World Gold Council (2011) *Gold Demand Trends: Third Quarter 2011*, World Gold Council, London.

Worthington, A. and Pahlavani, M. (2007) Gold investment as an inflationary hedge: cointegration evidence with allowance for endogenous structural breaks, *Applied Financial Economics Letters*, **3**, 259–62.

Yilmaz, K. (2010) Return and volatility spillovers among the East Asian equity markets, *Journal of Asian Economics*, **21**, 304–13.