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# Time-varying volatility spillovers between stock and precious metal markets with portfolio implications



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ABSTRACT

This paper investigates the time-varying risk spillovers between precious metals (gold, silver, palladium, and platinum) and major stock markets (USA, Japan, Europe and Asia) using the spillover index of Diebold and Yilmaz (2012). We also analyze asset allocations, hedge ratios, and hedging strategies. The results show evidence of volatility spillovers between precious metal and stock markets. Further, all the stock markets (except for Japanese market) are a source of volatility spillovers and the four precious metal markets are net receipt of volatility spillovers during the Global Financial Crisis and European Sovereign Debt Crisis. Finally, we find evidence of cross-market hedging, asset allocation, and hedging effectiveness.

#### 1. Introduction

The risk spillovers across international markets are an important research topic for market participants and researchers. This issue has several important practical implications in terms of asset allocation, hedging, market efficiency, and portfolio risk management. However, the effect of information transmission (both return and risk) is more visible during financial market turmoil. In fact, cross-market linkages increase sharply following crisis periods, indicating the presence of contagion effects, which reduce the benefits of international portfolio diversification. Following the Global Financial Crisis (GFC) of 2008-2009 and the European Sovereign Debt Crisis (ESDC) of 2010-2012, the matter of "flight-to-quality" has once again come back into sharp focus in the mind of investors and policymakers alike. For this reason, investors and portfolio managers find in precious metal markets an alternative way to effectively manage their portfolios, especially after the financialization of commodity markets and the increasing presence of financial investors in commodity markets. In fact, over the last decade, commodity futures have become a popular asset class for portfolio investors, just like stocks and bonds. In the empirical safe haven literature, gold is widely perceived as a good hedge and a safe haven asset in financial markets (Baur and Lucey, 2010; Baur and McDermott, 2010; Gürgün and Ünalmiş, 2014; Mensi et al., 2014a, 2015b). Lucey and Li (2015) document that silver, platinum and palladium act as a safe haven when gold does not.

Motivated by the aforementioned explanations, it is important to explore the precious metal-stock nexus and to check whether investors should include one or several precious metals in their portfolios for riskmanagement purposes. From the hedging and speculative prospective, precious metal commodities including gold and silver have been considered the most popular hedge assets for diversifying the exposure to portfolio risk (Skiadopoulos, 2012). However, gold and silver markets offer different volatilities and returns of lower correlation with conventional financial assets (stocks and bonds), especially if macroeconomic shocks tend to work on the precious metal assets and their portfolios in opposite directions (Baur and Lucey, 2010; Hood and Malik, 2013).

In addition, the recent and ongoing financial crisis and the attendant strength of precious metal commodity prices have renewed interest in understanding the fundamental process of information transmission between precious metals and stock markets (Chan et al., 2011; Chng, 2009; Creti et al., 2013). This effect was particularly intensified during the recent financial crises, which further implies that both volatility and correlations persistently move together over time (Sensoy et al., 2015; Silvennoinen and Thorp, 2013; Vivian and Wohar, 2012, among others). Apergis et al. (2014) examine the nature of spillovers between precious metal prices (gold and silver), stock markets, and macroeconomic variables for the G7 countries. They document substantial price transmissions across precious metal markets, stock markets, and the macroeconomy. Mensi et al. (2015a) investigate the time-varying linkages of a Saudi stock market with

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major commodity futures markets including WTI oil, gold, silver, wheat, corn, and rice. The authors suggest the usefulness of including commodities in a traditional portfolio of risk management for investors in the Saudi market. Therefore, investors are interested in examining the dynamics of metal commodity prices with the aim of designing strategies for optimal assets allocation, portfolio optimization, downside risk reduction, and hedging (Andreasson et al., 2016; Arouri et al., 2015; Belousova and Dorfleitner, 2012; Boako and Alagidede, 2016; Hammoudeh et al., 2014; Sadorsky, 2014, among others).

The purpose of this paper is to analyze the directional spillovers and net spillovers between stock markets (S & P 500 index, STOXX 600 index, Nikkei 225 index, TSX index, and DJASIA index) and precious metals (gold, silver, palladium, and platinum) over the period from January 4, 2000 to May 5, 2016. Further, we quantify the portfolio weights, hedge ratios as well as the hedging effectiveness for each precious metal-stock pair. The choice of those stock markets is motivated by their regions-the United States, Canada, Japan, Europe, and the Pacific Basin-and their global importance for equities and metal commodities. The S&P 500 index, STOXX 600 Europe index, Nikkei 225 index, TSX index, and DJASIA index are a benchmark for the United States, Europe, Japan, Canada, and the Pacific-Rim region, respectively. As for commodities, we select four major precious metal markets (gold, silver, palladium, and platinum) given their ability to protect investors during extreme negative stock market movements (Baur and Lucey, 2010; Baur and McDermott, 2010; Gürgün and Ünalmiş, 2014; Lucey and Li, 2015; Mensi et al., 2014a, 2015b). We also select these four precious metal markets due to the rising demand in these markets. Further, these precious metal markets are characterized by their liquidity. On the other hand, the variability of precious metal-stock price pairs has implications for the investors and the hedgers dealing with these markets. In fact, investors attempting to offset their exposures and risks against downturn market movements should adjust their hedge ratios and strategies in accordance with the movement of stock markets (bear or bull markets). Hence, we quantify the portfolio design and hedging strategies.

The paper makes at least four important contributions to the existing literature. First, it examines the time-varying correlation between stock and precious metal markets using a Dynamic Equicorrelation (DECO)-Fractionally Integrated GARCH (FIGARCH) model. This model is more flexible than the standard GARCH model as it considers a long-range memory process in the conditional variance of the financial time series and assumes an evolving correlation among financial assets. DECO assumes that each pair of returns in a system display the same correlation that changes over time. Second, it explores the directional spillovers and net spillovers across stock and precious metal markets using the spillover index developed by Diebold and Yilmaz (2012). In addition, we analyze a rolling sample approach to detect the time-varying dynamics of the spillover index given that the recent financial crises may directly affect volatility structures between stock and precious metal futures markets. The rolling sample approach allows one to examine the risk spillovers between precious metal and stock markets through time. When studying the stock-commodity nexus, we observe instability due to structural breaks which is captured by the rolling sample approach (Nyakabawo et al., 2015). Third, we study the net spillover index and the sensitivity of the spillover index for robustness. Finally, we quantify the optimal portfolio weights, hedge ratios, and hedging effectiveness for the stock and precious metal portfolios.

Using the Diebold and Yilmaz (2012) spillover index, our empirical results indicate strong evidence of significant volatility spillovers between precious metal and stock markets. Moreover, we find that all stock indexes are a source of volatility spillovers with the exception of Nikkei 225 index. In addition, all precious metal markets are net recipients of volatility spillovers during the GFC and ESDC. Finally, we find evidence of crossmarket hedging, asset allocation, and hedging strategies.

The remainder of this study is organized as follows. Section 2 discusses the methodology used in this study. Section 3 describes the data and conducts some preliminary analysis. Section 4 reports and discusses the empirical results. Section 5 draws implications for risk management. Section 6 provides concluding remarks.

#### 2. Empirical method

This section describes the study's empirical methods. It begins with a multivariate DECO-FIGARCH model, which measures equicorrelation between stock and precious metal futures markets. To some extent, we also employ the spillover index of Diebold and Yilmaz (2012), which identifies the dynamics of directional volatility spillovers across stock and precious metal futures markets.

#### 2.1. The DECO-FIGARCH model

We assume that the return-generating process can be described by an AR (1) model in which the dynamics of current stock returns are explained by their lagged returns. The AR (1) model is defined as follows:

$$r_t = \mu + \psi r_{t-1} + \varepsilon_t, \quad t \in T, \quad \text{with} \quad \varepsilon_t = z_t \sqrt{h_t}, \quad z_t \sim N(0, 1), \tag{1}$$

where  $|\mu| \in [0, \infty)$ ,  $|\psi| < 1$ , and the innovations  $\{z_t\}$  are an independently and identically distributed (*i. i. d.*) process. Next, we estimate the conditional volatilities  $h_t^2$  from the univariate FIGARCH (*p*, *d*, *q*) process specified in Eq. (2).

$$\phi(L)(1-L)^{d}\varepsilon_{t}^{2} = \omega + [1-\beta(L)](\varepsilon_{t}^{2}-h_{t}^{2}), \qquad (2)$$

where  $(1 - L)^d$  is the fractional differencing operator. The longmemory parameter *d* satisfies the condition  $0 \le d \le 1$ ,  $\phi(L)$  and  $\beta(L)$ are finite-order lag polynomials with roots assumed to lie outside the unit circle. To obtain dynamic correlations between the analyzed variables, we review the DCC model of Engle (2002). Assume that  $E_{t-1}[\varepsilon_t] = 0$  and  $E_{t-1}[\varepsilon_t\varepsilon'_t] = 0$ , where  $E_t[\cdot]$  is the conditional expectation for using the information set available at time *t*. The conditional variance-covariance matrix,  $H_t$ , can be written as:

$$H_t = D_t^{1/2} R_t D_t^{1/2}, (3)$$

where  $R_t = [\rho_{ij,t}]$  is the conditional correlation matrix, while the diagonal matrix of the conditional variances is given by  $D_t = diag(h_{i,t}, ..., h_{n,t})$ . Engle (2002) models the right-hand side of Eq. (3), rather than  $H_t$ , directly by proposing the following dynamic correlation structure:

$$R_t = \{Q_t^*\}^{-1/2} Q_t (Q_t^*)^{-1/2}, \tag{4}$$

$$Q_t^* = diag[Q_t],\tag{5}$$

$$Q_t = [q_{ij,t}] = (1 - a - b)S + au_{t-1}u'_{t-1} + bQ_{t-1},$$
(6)

where  $u_t = [u_{1,t}, ..., u_{n,t}]'$  is the standardized residuals (i.e.,  $u_{i,t} = \varepsilon_{i,t}/h_{i,t}$ ,  $S \equiv [s_{i,j}] = E[u_t u'_t]$  is the  $n \times n$  unconditional covariance matrix of  $u_t$ , and a and b are non-negative scalars satisfying a + b < 1). The resulting model is called the DCC model.

In this context, Aielli (2013) proves that the estimation of the covariance matrix  $Q_t$  in this way is inconsistent because  $E[R_t] \neq E[Q_t]$ , and suggests the following consistent model (cDCC model) for the correlation-driving process:

$$Q_{t} = (1 - a - b)S^{*} + a(Q_{t-1}^{*})^{1/2}u_{t-1}u_{t-1}^{*}Q_{t-1}^{*}) + bQ_{t-1},$$
(7)

where  $S^*$  is the unconditional covariance matrix of  $Q_t^{*1/2}u_t$ .

Engle and Kelly (2012) suggest that we model  $\rho_t$  by using the cDCC process to obtain conditional correlation matrix  $Q_t$  and then taking the mean of its off-diagonal elements. This approach, which reduces estimation time, is called the dynamic equicorrelation (DECO) model. The scalar equicorrelation is defined as:

$$\rho_t^{DECO} = \frac{1}{n(n-1)} (J'_n R_t^{cDCC} J_n - n) = \frac{2}{n(n-1)} \sum_{i=1}^{n-1} \sum_{j=i+1}^n \frac{q_{ij,i}}{\sqrt{q_{ii,i} q_{jj,i}}}$$
(8)

where  $q_{ij,t} = \rho_t^{DECO} + a^{DECO}(u_{i,t-1}u_{j,t-1} - \rho_t^{DECO}) + b^{DECO}(q_{ij,t} - \rho_t^{DECO})$ , which is the (i, j)th element of the matrix  $Q_t$  from the cDCC model.

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