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Does uncertainty move the gold price? New evidence from a nonparametric causality-in-quantiles test ☆

Mehmet Balcilar [a,b,d], Rangan Gupta [b,*], Christian Pierdzioch [c]

[a] Department of Economics, Eastern Mediterranean University, Famagusta, via Mersin 10, Northern Cyprus, Turkey and Department of Economics, University of Pretoria, Pretoria, 0002, South Africa
[b] Department of Economics, University of Pretoria, Pretoria, 0002, South Africa
[c] Department of Economics, Helmut Schmidt University, Holstenhofweg 85, P.O.B. 700822, 22008 Hamburg, Germany
[d] IPAG Business School, Paris, France

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ABSTRACT

Much significant research has been done to study the links between gold returns and the returns of other asset classes in times of economic crisis and high uncertainty. We contribute to this research by using a novel nonparametric causality-in-quantiles test to study how measures of policy and equity-market uncertainty affect gold-price returns and volatility. For daily and monthly data, we find evidence of causality running from various uncertainty measures to both gold returns and volatility. For quarterly data, evidence of causality weakens and is significant only for some uncertainty measures and only for gold volatility.

1. Introduction

Media reports and investment recommendations often emphasize that gold acts as a classic safe-haven and hedging investment in times of economic and political uncertainty. It is, therefore, not surprising that researchers have analyzed extensively the safe-haven and hedging properties of gold investments in times of financial crisis and market jitters (Baur and McDermott 2010, Baur and Lucey 2010, among others). Less is known, however, about how gold returns and gold volatility react to measures of economic and political uncertainty.

Studying the link between gold-price movements and measures of economic and political uncertainty is interesting because gold investments may act as a hedge against fluctuations in various variables like bond prices, stock prices, exchange rates, the oil price, and inflation (Beckmann and Czudaj 2013a, 2013b, Beckmann et al. 2015, Ciner et al. 2013, Reboredo 2013a, 2013b, to name just a few). Changes in economic and political uncertainty, in turn, are likely to affect, to a differing extent, all these variables and, thus, may be a more fundamental driver of the gold price than, for example, exchange rates or the oil price. In fact, recent studies by Colombo (2013), Jones and Olson (2013), Kang and Ratti (2013), Baker et al., (2015), and Balcilar et al., (2016) show that news-based uncertainty affects not only macro variables like output and inflation but also exchange rates, stock prices, and the oil price. Hence, rather than testing for the individual effects of movements in these variables on gold-price movements it is interesting to study directly how gold returns and gold volatility react to economic and political uncertainty. Our first contribution to the literature on the gold price, thus, is that, rather than focusing on specific episodes of market turbulence or specific asset classes, we ask how broad measures of economic and political uncertainty affect gold-price returns and volatility. We measure economic and political uncertainty using the widely-studied uncertainty indexes constructed by Baker et al. (2015), Jurado et al. (2015), and Rossi and Sekhposyan (2015).

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* Corresponding author.
E-mail addresses: mehmet@mbalcilar.net (M. Balcilar), rangan.gupta@up.ac.za (R. Gupta), c.pierdzioch@hsu-hh.de (C. Pierdzioch).

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Our second contribution to the literature on the gold price is that we use a novel nonparametric causality-in-quantiles test recently proposed by Balcilar et al. (forthcoming) to study whether uncertainty causes gold-price returns and volatility. Their test integrates the test for nonlinear causality of k-th order developed by Nishiyama *et al.* (2011) with the quantile-causality test advanced by Jeong *et al.* (2012) and, hence, can be considered to be a generalization of the former. The causality-in-quantiles test is an integrated modeling platform that renders it possible (i) to test for causal effects across all quantiles of the distribution of gold-price movements, and, (ii) to test not only for causality in first moments (returns) but also for higher-order causality in second moments (volatility). Our decision to use a nonparametric causality-in-quantiles test to study whether uncertainty causes gold-price returns and volatility is motivated by results of earlier research that clearly show that the structure of dependence of gold returns on the returns of other asset classes is likely to vary across the conditional distribution of gold-price movements (Baur 2013, Ciner et al. 2013, among others).

We organize the remainder of this research note as follows. In Section 2, we describe the causality-in-quantiles test. In Section 3, we describe our data and empirical results. Finally, in Section 4, we offer some concluding remarks.

2. Methodology

We present a novel methodology, as proposed by Balcilar et al. (forthcoming), for the detection of nonlinear causality via a hybrid approach based on the frameworks of Nishiyama et al. (2011) and Jeong et al. (2012). We denote gold returns as y_t and the uncertainty indexes studied in this research as x_t. Following Jeong et al. (2012), the variable x_t does not cause y_t in the θ-quantile with respect to the lag-vector of $\left\{y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}\right\}$ if[1]

$$Q_\theta\left(y_t y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}\right)=Q_\theta\left(y_t y_{t-1}, \ldots, y_{t-p}\right) \tag{1}$$

x_t is a prima facie cause of y_t in the θ-th quantile with respect to $\left\{y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}\right\}$ if

$$Q_\theta\left(y_t y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}\right)\neq Q_\theta\left(y_t y_{t-1}, \ldots, y_{t-p}\right) \tag{2}$$

where $Q_\theta(y_t \bullet)$ is the θ-th quantile of y_t depending on t and $0<\theta<1$.

Let $Y_{t-1}\equiv(y_{t-1}, \ldots, y_{t-p})$, $X_{t-1}\equiv(x_{t-1}, \ldots, x_{t-p})$, $Z_t=(X_t, Y_t)$ and $F_{y_t|Z_{t-1}}(y_t \mid Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t \mid Y_{t-1})$ denote the conditional distribution functions of y_t given Z_{t-1} and Y_{t-1}, respectively. The conditional distribution $F_{y_t|Z_{t-1}}(y_t \mid Z_{t-1})$ is assumed to be absolutely continuous in y_t for almost all Z_{t-1}. If we denote $Q_\theta(Z_{t-1})\equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1})\equiv Q_\theta(y_t|Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1}) \mid Z_{t-1}\}=\theta$ with probability one. Consequently, the hypotheses to be tested based on the definitions in Eqs. (1) and (2) are

$$H_0: P\left\{F_{y_t|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right) \mid Z_{t-1}\right\}=\theta\right\}=1 \tag{3}$$

$$H_1: P\left\{F_{y_t|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right) \mid Z_{t-1}\right\}=\theta\right\}<1 \tag{4}$$

Jeong et al. (2012) use the distance measure $J=\{\varepsilon_t E(\varepsilon_t \mid Z_{t-1}) f_Z(Z_{t-1})\}$, where ε_t is a regression error and $f_Z(Z_{t-1})$ is the marginal density function of Z_{t-1}. The regression error, ε_t, emerges based on the null in Eq. (3), which can only be true if and only if $E\left[1\{y_t\leq Q_\theta(Y_{t-1}) Z_{t-1}\}\right]=\theta$ or equivalently $1\{y_t\leq Q_\theta(Y_{t-1})\}=\theta+\varepsilon_t$, where $1\{\bullet\}$ is the indicator function. Jeong et al. (2012) specify the distance function as follows:

$$J=E\left[\left\{F_{y_t|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right) \mid Z_{t-1}\right\}-\theta\right\}^2 f_Z(Z_{t-1})\right] \tag{5}$$

In Eq. (3), it is important to note that $J \geq 0$, i.e., we have $J=0$ with equality if and only if H_0 in Eq. (5) is true, while $J>0$ holds under the alternative H_1 in Eq. (4). Jeong et al. (2012) show that the feasible kernel-based test statistic for J has the following form:

$$\hat{J}_T=\frac{1}{T(T-1)h^{2p}}\sum_{t=p+1}^{T}\sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1}-Z_{s-1}}{h}\right)\hat{\varepsilon}_t\hat{\varepsilon}_s \tag{6}$$

where $K(\bullet)$ is the kernel function with bandwidth h, T is the sample size, p is the lag-order, and $\hat{\varepsilon}_t$ is the estimate of the unknown regression error, estimated as

$$\hat{\varepsilon}_t=1\left\{y_t\leq\hat{Q}_\theta\left(Y_{t-1}\right)\right\}-\theta \tag{7}$$

$\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θ-th conditional quantile of y_t given Y_{t-1}. We estimate $\hat{Q}_\theta(Y_{t-1})$ using the nonparametric kernel method as

$$\hat{Q}_\theta\left(Y_{t-1}\right)=\hat{F}^{-1}_{y_t|Y_{t-1}}\left(\theta Y_{t-1}\right) \tag{8}$$

where $\hat{F}_{y_t|Y_{t-1}}(y_t Y_{t-1})$ is the *Nadarya-Watson* kernel estimator given by

$$\hat{F}_{y_t|Y_{t-1}}\left(y_t Y_{t-1}\right)=\frac{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)1\left(y_s\leq y_t\right)}{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)} \tag{9}$$

with $L(\bullet)$ denoting the kernel function and h the bandwidth.

In an extension of the Jeong et al. (2012) framework, we develop a test for the 2nd moment. To this end, we use the nonparametric Granger-quantile-causality approach by Nishiyama et al. (2011). In order to illustrate the causality in higher-order moments assume that:

$$y_t=g\left(Y_{t-1}\right)+\sigma\left(X_{t-1}\right)\varepsilon_t \tag{10}$$

where ε_t is a white noise process, and $g(\bullet)$ and $\sigma(\bullet)$ are unknown functions that satisfy certain conditions for stationarity. However, this specification does not allow for Granger-type causality testing from x_t to y_t, but could possibly detect the "predictive power" from x_t to y_t^2 when $\sigma(\bullet)$ is a general nonlinear function. Hence, the Granger causality-in-variance definition does not require an explicit specification of squares for X_{t-1}. We reformulate Eq. (10) into a null and alternative hypothesis for causality in variance as follows:

$$H_0: P\left\{F_{y_t^2|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right) \mid Z_{t-1}\right\}=\theta\right\}=1 \tag{11}$$

$$H_1: P\left\{F_{y_t^2|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right) \mid Z_{t-1}\right\}=\theta\right\}<1 \tag{12}$$

To obtain a feasible test statistic for testing the null hypothesis in Eq. (11), we replace y_t in (Eq. (6)–9) with y_t^2. Incorporating the Jeong et al. (2012) approach we overcome the problem that causality in the conditional 1st moment (mean) imply causality in the 2nd moment (variance). In order to overcome this problem, we interpret the causality in higher-order moments using the following model:

$$y_t=g\left(X_{t-1}, Y_{t-1}\right)+\varepsilon_t \tag{13}$$

Thus, higher- order quantile causality can be specified as:

[1] The exposition in this section closely follows Nishiyama et al. (2011) and Jeong et al. (2012).