Does Uncertainty Move the Gold Price? New Evidence From a Nonparametric Causality-in-Quantiles Test

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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.

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1. Introduction

Much significant research has been done to study various facets of the link between gold returns and the returns of other asset classes in times of financial crisis and market jitters (Baur and McDermott 2010, Baur and Lucey 2010, Ciner *et al.* 2013, Beckmann *et al.* 2015, among others). A common approach in this strand of research is to identify market jitters in terms of the quantiles of the distribution of, for example, stock or bond returns. Another widely-studied approach is to use quantile regressions to inspect how the structure of dependence of gold returns on the returns of other asset classes varies across the entire conditional distrubtion of gold-price movements (Baur 2013, Zagaglia and Marzo 2013, among others). We build on the quantile-regression approach but go beyond earlier research in two important respects.

First, rather than focusing on specific episodes of market turbulence, 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). Second, 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).

We organize the remainder of this paper as follows. In Section 2, we describe the causality-in-quantiles test. In Section 3, we describe our data and empirical results. Finally, in Section4, 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 $\{y_{t-1},...,y_{t-p},x_{t-1},...,x_{t-p}\}$ if[1]

$$Q_\theta\{y_t \mid y_{t-1},...,y_{t-p},x_{t-1},...,x_{t-p}\} = Q_\theta\{y_t \mid y_{t-1},...,y_{t-p}\} \tag{1}$$

x_t is a prima facie cause of y_t in the θth quantile with respect to $\{y_{t-1},...,y_{t-p},x_{t-1},...,x_{t-p}\}$ if

$$Q_\theta\{y_t \mid y_{t-1},...,y_{t-p},x_{t-1},...,x_{t-p}\} \neq Q_\theta\{y_t \mid y_{t-1},...,y_{t-p}\} \tag{2}$$

where $Q_\theta\{y_t \mid \cdot\}$ is the θth quantile of y_t depending on t and $0<\theta<1$.

Let $Y_{t-1} \equiv (y_{t-1},...,y_{t-p})$, $X_{t-1} \equiv (x_{t-1},...,x_{t-p})$, $Z_t = (X_t, Y_t)$ and $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t, Y_{t-1})$ denote the conditional distribution functions of y_t given Z_{t-1} and Y_{t-1} respectively. The conditional distribution $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$ is assumed to be absolutely continuous in y_t for almost all Z_{t-1}. If we denote $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t \mid Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t \mid Y_{t-1})$, 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

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

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

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 $E[\mathbf{1}\{y_t \le Q_\theta(Y_{t-1}) \mid Z_{t-1}\}] = \theta$ or equivalently $\mathbf{1}\{y_t \le Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is the indicator function. Jeong *et al.* (2012) specify the distance function as follows:

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

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

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 $K(\cdot)$ 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

$$\hat{\varepsilon}_t = 1\{y_t \leq Q_\theta(Y_{t-1}) - \theta\} \tag{7}$$

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

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

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

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

with $L(\cdot)$ 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). For a y_t process, they assume that:

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

where ε_t is a white noise process, and $g(\cdot)$ and $\sigma(\cdot)$ are unknown functions that satisfy certain conditions for stationarity. However, this specification not onlyallows 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 $\sigma(\cdot)$ 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 re-formulate Eq. (10) into a null and alternative hypothesis for causality in variance as follows:

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

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

To obtain a feasible test statistic for testing the null hypothesis in Eq. (10), 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 specify the causality in higher-order moments using the following model:

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

Thus, higher order quantile causality can be specified as:

$$H_0 = P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1}) \mid Z_{t-1}\} = \theta\} = 1 \qquad \text{for } k = 1,2,\ldots,K \tag{14}$$

$$H_1 = P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1}) \mid Z_{t-1}\} = \theta\} < 1 \qquad \text{for } k = 1,2,\ldots,K \tag{15}$$

Integrating the entire framework, we define that x_t *Granger causes* y_t *in quantile* θ *up to the* K *th moment* utilizing Eq. (11) to construct the test statistic of Eq. (6) for each k. However, it can be shown that it is not easy to combine the different statistics for each $k = 1, 2, \ldots, K$ into one statistic for the joint null in Eq. (14) because the statistics are mutually correlated (Nishiyama *et al.* 2011). To efficiently address this issue, we include a sequential-testing method as described by Nishiyama *et al.* (2011) with some modifications. Firstly, we test for nonparametric Granger causality in the 1st moment $(k = 1)$. Failure to reject the null for $k = 1$, does not automatically lead to noncausality in the 2nd moment and, thus, we construct the tests for $k = 2$. Finally, we can test for the existence of causality-in-variance, or the causality-in-mean and variance successively.

The empirical implementation of causality testing via quantiles entails specifying three important choices: the bandwidth h, the lag order p, and the kernel type for $K(\cdot)$ and $L(\cdot)$ in

Eq. (6) and (9). We determine the lag order using the Schwarz Information Criterion (SIC) under a VAR comprising gold returns and uncertainty.[2] The bandwidth value is selected using the least squares cross-validation method. Lastly, for $K(\cdot)$ and $L(\cdot)$, we employ Gaussian kernels.

3. Data and empirical results

Our analysis is based on two variables: the returns of the gold price and alternative measures of uncertainty, measured at daily, monthly, and quarterly frequency. The gold returns are measured in terms of the first-differenced natural logarithm of the gold fixing price at 3:00 P.M. (London time) in the London Bullion Market, based in U.S. Dollars, which is obtained from the FRED database of the Federal Reserve Bank of St. Louis. We obtain the gold-price data at a daily frequency, and then average over months and quarters to match the frequencies of the measures of uncertainty.

In order to measure uncertainty, we start with data compiled and disseminated by Baker *et al.* (2015).[3] Specifically, we use daily data on economic-policy uncertainty and daily data on equity-market uncertainty. Economic policy uncertainty and equity market uncertainty are news-based indexes that use data from over 1000 newspapers from Access World New's NewsBank. Equity-market uncertainty is based on searches of newspaper articles that contain the terms "uncertainty" or "uncertain", "economic" or "economy" and one or more of the following terms: "equity market", "equity price", "stock market", or "stock price". Economic-policy uncertainty, instead of the third set of terms used to construct equity-market uncertainty, includes terms related to "legislation" or "deficit" or "regulation" or "congress" or "Federal Reserve" or "White House". Monthly data on the economic policy uncertainty index are also available from Baker *et al.* (2015). The monthly economic-policy uncertainty index quantifies newspaper coverage of three types of news: policy-related economic uncertainty, the number of federal tax code provisions set to expire in future years, and disagreement among economic forecasters.

We also study the uncertainty indexes developed by Jurado *et al.* (2015).[4] Their uncertainty indexes (available at forecast horizons of 1, 3 and 12 months) are based on a factors-based approach applied on a data rich-environment to provide direct econometric estimates of time-varying macroeconomic uncertainty. Finally, we use the quarterly data on uncertainty developed

[2] The parsimonious lag-selection based on the SIC criterion is used to prevent overparameterization problems associated with nonparametric approaches.
[3] The data were downloaded from: http://www.policyuncertainty.com.
[4] The data are downloadable from http://www.econ.nyu.edu/user/ludvigsons/.

by Rossi and Sekhposyan (2015).[5] Their data measure how unexpected a realization of a representative macroeconomic variable is relative to the unconditional forecast error distribution. They use forecast error distributions based on the nowcasts and forecasts of the Survey of Professional Forecasters. Their data feature a revised measure of uncertainty and also a real-time measure at forecast horizons of 1 and 4-quarters-ahead. In addition, data are also available for upside and downside uncertainty, which, in turn are based on news or outcomes that are unexpectedly positive or negative, respectively.

We work with natural logarithmic levels of the various uncertainty indexes, as we found that they are stationary based on standard unit root tests.[6] Hence, the basic condition of stationarity of the variables required for our causality-in-quantiles approach holds for gold returns and the various uncertainty indexes.

Based on availability of the variables being studied, the daily data on gold returns and economic-policy uncertainty and equity-market uncertainty cover the period from 2nd January, 1985 to 11th November, 2015. As for the monthly data, the sample period is 1968:05-2014:12, when we use the uncertainty indexes at horizons of 1, 3 and 12 of Jurado *et al.*, (2015). When we use the Baker *et al.* (2015) measures of uncertainty, the sample period is 1968:05-2014:10 and a shorter sample of 1985:01-2015:10. Finally, when we use the quarterly uncertainty indexes of Rossi and Sekhposyan (2015), the revised data cover the sample periods 1968:04-2015:02 and 1968:04-2014:02 for forecast horizons of 1 and 4 quarters respectively. When we use the real-time measures of uncertainty, the sample period is 1985:01-2015:02 and 1985:01-2014:02 for horizons of 1 and 4 quarters respectively.

-- Please include Figures 1 – 3 about here. --

Our empirical findings can be summarized as follows in Figures 1-3 for daily, monthly, and quarterly data, respectively. First, when we study the uncertainty indexes compiled by Baker *et al.* (2015) in Figure 1(a), for daily data on economic-policy uncertainty, we find strong evidence of causality across a broad range of quantiles from economic-policy uncertainty to gold volatility. Daily data on equity-market uncertainty in Figure 1(b) show that uncertainty causes both gold returns and volatility, also for a broad range of quantiles. For both economic-policy and equity-

[5] The data is available at: http://www.tateviksekhposyan.org/.

[6] Theoretically, measures of uncertainty should be stationary. However, statistically deviations from stationarity could arise in specific sample periods. Unit-root tests revealed that the natural logarithm of the uncertainty measures do not contain unit roots and, hence, can be used in levels in our analysis. Complete details of the unit-root tests are available upon request from the authors.

market uncertainty, the strength of the evidence of causality from uncertainty to volatility exhibits an inverted u-shaped pattern across quantiles. Similar observations can be made in terms of predictability for both gold returns and volatility when we look at the monthly economic-policy uncertainty data covering the longer span of 1968:05-2014:10, as captured in Figure 2(a). However, as shown in Figure 2(b) there is no evidence of predictability for either gold returns or volatility from the economic-policy uncertainty index over the period 1985:01-2015:10. For the uncertainty indexes constructed by Jurado *et al.* (2015), available at a monthly frequency and at various forecast horizons, we also find an inverted u-shaped pattern which, however, arises for both first and second moments of gold-price fluctuations as plotted in Figures 2(c) to 2(e). In addition, we find an asymmetry insofar as the evidence of causality for both first and second moments of gold-price fluctuations is stronger for quantiles larger than 0.5 than for smaller quantiles. Finally, the results for the uncertainty indexes developed by Rossi and Sekhposyan (2015), with results of predictability plotted in Figures 3(a)-3(l), corroborate the existence of an inverted u-shaped pattern of causality, where the significance of this u-shaped pattern depends on the data being studied. The u-shaped causality pattern is significant for gold volatility for one-quarter-ahead revised, and for the one-quarter-ahead and four-quarter-ahead real-time uncertainty. Further evidence of predictability of gold returns volatility is detected for four-quarter-ahead revised upside uncertainty. There is some evidence of causality of gold volatility for a small range of quantiles for four-quarter-ahead revised downside uncertainty. Finally, results indicate the existence of causality of gold volatility for four-quarter-ahead real-time upside uncertainty. Overall, while causality from various measures of uncertainty for both gold returns and volatility exists for higher-frequency data (daily and monthly), the same exists for various specifications only for gold volatility at a quarterly frequency.

4. Concluding remarks

We have studied at various data frequencies and for various sample periods the causal effects of several uncertainty measures on the first and second moments of gold-price fluctuations based on a novel causality-in-quantiles test. We find an inverted u-shaped pattern of causality across quantiles, but also that the details of the results differ across the various uncertainty measures considered in the recent literature. Evidence of causality is stronger for the second than for the first moment (for which the test results for the economic-policy uncertainty index are insignificant) of gold-price fluctuations when we study the uncertainty indexes of Baker *et al.* (2013) at a daily frequency, and also at monthly frequency that covers a longer span of data, and the quarterly uncertainty indexes of Rossi and Sekhposyan (2015).

In future research, our empirical analysis can be extended in several directions. One interesting direction for future research is to explore whether the evidence of causality-in-quantiles we have reported in this research can be used by investors to set up a profitable trading strategy. Our results are silent in this respect because we have only studied the causal effects of uncertainty on gold returns and gold volatility, but we have not directly explored the implications of our empirical results, for example, for the the safe-haven property of gold investments. Another closely related direction for future research is to explore the implications of the implications of causality-in-quantiles for the predictability of gold-price fluctations. In the recent literature on the predictability of gold-price fluctations, quantiles-based techniques have been studied by Pierdzioch et al. (2016). They, however, have not studied whether the uncertainty indexes that we have studied in this research help to forecast gold-price fluctuations. A natural extension of their research, thus, is to add uncertainty indexes as a predictor in their forecasting model and to study how often it is incorporated in a forecasting model when one seeks to forecast different quantiles of the conditional distribuiton of gold-price fluctations.

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Figure 1. Results for the Baker *et al.* (2015) daily uncertainty indexes

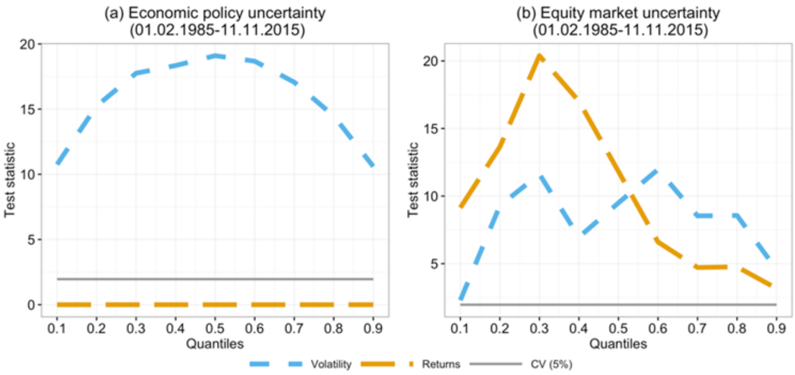

Figure2. Results for the Baker *et al.* (2015) [Figures 2(a)-2(b)] and Jurado *et al.* (2015) [Figures 2(c)-2(e)] monthly uncertainty indexes

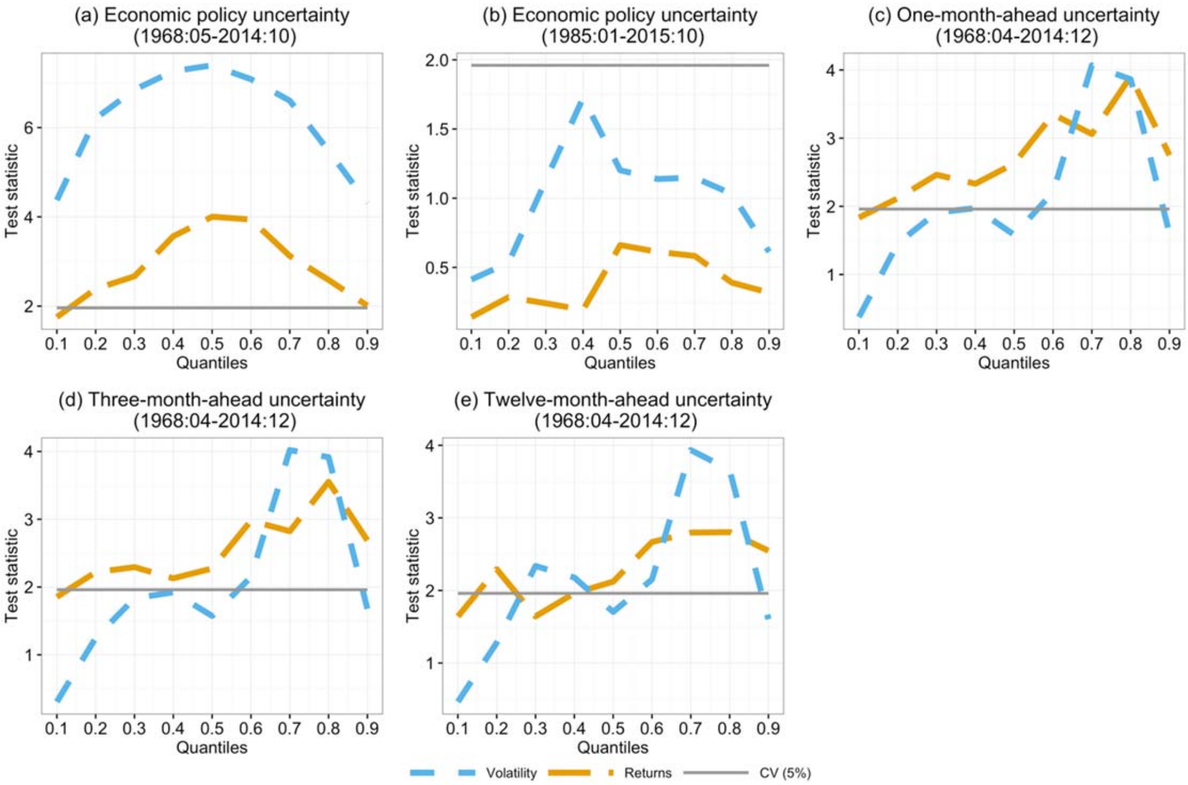

Figure 3. Results for the Rossi and Sekhposyan (2015) quarterly uncertainty indexes