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Abstract
This paper utilises the newly proposed nonparametric causality-in-quantiles test to examine the predictability of returns and the volatility of gold based on inflation for G7 countries. The causality-in-quantiles approach permits us to test for not only causality in mean but also causality in variance. We start our investigation by utilising tests for nonlinearity. These tests identify nonlinearity, as the linear Granger causality tests are subject to misspecification error. Unlike tests of misspecified linear models, our nonparametric causality-in-quantiles tests find causality in mean and variance from inflation to gold returns via quantiles 0.20 to 0.70, implying that very low- and high-return movements in gold markets are not related to inflation. These changes in low- and high-level gold returns should be related to other sources, such as financial shocks and exchange market shocks. We find support that gold serves as a hedge against inflation, but only in the mid-quantile ranges, i.e., quantiles 0.20 to 0.70. Our results show that gold does not serve as a hedge against inflation during periods when gold returns are very low or very high, which are respectively quiet and highly volatile periods.

Keywords: Gold, Inflation, Spot and futures markets; Quantile causality.
JEL Codes: C22, Q02, E31.

1. Introduction

Gold, the oldest medium of exchange, is a popular hedge (Chang et al. 2013), has symbolic value (Godness et al. 2016), is a broad measure of economic conditions (Natanelov et al. 2011) and is the only true standard of value, even in war and crisis times. It has a great impact on economies and is commonly considered to be a safe haven for investment. As it holds its value independently of domestic politics, its stability against fluctuating currencies and people's high interest and confidence over the centuries, the global gold market and its interdependency with other commodities and economic dynamics have always attracted a great deal of economic curiosity. Moreover, due to its high profit potential and remarkable risk protection feature, the gold market is receiving increasing attention (Zhang and Wei, 2010). Therefore, consistent interest in the gold market has necessitated inquiry regarding its relationship with other macro-economic factors, such as oil and inflation. This study investigates the relationship between gold prices and inflation using a novel methodology (Balcilar et al. 2016a, b) that is useful in detecting nonlinear causality.

Although there is a large body of research that either supports the role of gold as a traditional hedge against inflation (Jaffe 1989, Dempster and Artigas 2009, Narayan et al. 2010, Ghosh 2011) or not (Soytas et al. 2009) and as a hedge in bond and stock markets (Baur and Lucey 2010), relatively few studies have investigated the causal relationship between inflation and gold prices. To our knowledge, no study has employed the nonparametric quantile-based test that we use in this study. The nonparametric causality-in-quantiles test we use is robust to nonlinearities, structural breaks and outliers.

Despite the limited body of literature regarding the link between gold and inflation, several studies have analysed the impact of gold prices on predicting inflation (Mahdavi and Zhou 1997), the hedging effectiveness of gold and its ability to forecast future inflation (Godness et al. 2016, Beckmann and Czudaj 2013, Wanga et al. 2011), the long-term relationship between the price of gold and inflation (Ghosh et al. 2004, Worthington and Pahlavani 2007), the accuracy of gold as an indicator of future inflation over other measures (such as consumer price index and oil), its effectiveness in gauging and combating the effects of inflation on a portfolio (Ranson, 2005), the ineffectiveness of unexpected changes in the CPI in relation to gold prices (Blose, 2010) or the use of inflation to examine the dependence structure and linkages between gold and other commodity markets, especially oil (Zhang and Wei 2010, Narayan et al. 2010, Reboredo 2013, Tiwari and Sahadudheen 2015).

The purpose of this study is to examine the Granger causality in mean and variance from inflation to gold prices in G7 countries using the nonparametric causality-in-quantiles test. Evidence from available studies is mixed, which could be due to the different country-specific case studies, data samples and methodologies, and misspecification errors. However, no insightful work has been done yet to examine the dynamic link between inflation and gold prices. To address that gap in the literature, we utilise the novel nonparametric causality-in-quantiles test of Balcilar et al. (2016a, b) to study the predictability of the conditional mean and variance of gold returns based on inflation. The nonparametric causality-in-quantiles test combines the test for the nonparametric causality of the k^{th} order by Nishiyama et al. (2011) with the causality-in-quantiles test by Jeong et al. (2012) and, hence, can be thought of as a generalization of the former. The causality-in-quantiles approach used in this study is novel in three ways. First, it is robust to misspecification errors, as it detects the underlying linear and nonlinear dependence structure in the time series under examination. Second, using this approach, one can test not only causality in mean (1^{st} moment) but also causality in variance (2^{nd} moment). Thus, higher-order dependency can be studied. Such an examination is vital in light of the fact that, during some periods, causality in the conditional mean may not exist, whereas higher-order interdependencies may be significant. This method enables us to test the mean and variance causality links from inflation to gold price returns.

We use monthly data from the December 1979-August 2016 period. To the best of our knowledge, this is the first study to analyse the predictability of returns and the volatility of gold returns based on inflation using the nonparametric causality-in-quantiles method. Causality-in-quantiles tests usually find causality from the 0.20 to 0.70 quantiles, meaning that very low- and high-return movements in gold markets are not related to inflation. These results should be connected to different factors such as financial shocks and exchange market shocks. The empirical evidence shows that gold serves as a hedge against inflation, a commonly known fact. The causality is not only in the mean (returns) but also in the variance, meaning that inflation impacts both mean gold returns and gold market volatility.

The rest of the paper is organized in the following manner. Section 2 explains the methodology. Section 3 presents the data and empirical evidence. Finally, Section 4 concludes the paper.

2. Methodology

We utilise the nonparametric causality-in-quantiles approach of Balcilar et al. (2016a, b), a novel method that expands upon the approaches of Nishiyama et al. (2011) and Jeong et al. (2012). This methodology is capable of accounting for nonlinear causality in quantiles through a hybrid approach. The returns on gold are denoted as y_t, and inflation is denoted as x_t. As described in Jeong et al. (2012), we characterize quantile-based causality as follows[1]: x_t does not cause y_t in the θ^{th} quantile with respect to the lag vector of $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$ if

$$Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}) = Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}) \quad (1)$$

x_t is presumably the cause of y_t in the θ^{th} quantile with regard to $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$ if

$$Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}) \neq Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}) \quad (2)$$

Here, $Q_\theta(y_t| \cdot)$ is the θ^{th} quantile of y_t. The conditional quantiles ofy_t, $Q_\theta(y_t| \cdot)$, depends on t, and the quantiles are constrained between zero and one, i.e., $0 < \theta < 1$.

For a compact presentation of the causality-in-quantiles tests, we define the following vectors: $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, and $Z_t = (X_t, Y_t)$. Additionally, we define the conditional distribution functions $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t|Y_{t-1})$, with the distribution functions of y_t conditioned on vectors Z_{t-1} and Y_{t-1}, respectively. Moreover, the conditional distribution function $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ is assumed to be continuous in y_t for almost all Z_{t-1}. By defining $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we can see that $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$, which holds true with a probability equal to one.

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

Subsequently, the hypotheses to be tested for causality in quantiles, taking into account conditions (1) and (2), can be stated as:

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

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

To define a measurable metric for the practical implementation of the causality-in-quantiles tests, Jeong et al. (2012) use the distance measure $J = \{\varepsilon_t E(\varepsilon_t|Z_{t-1}) f_Z(Z_{t-1})\}$, where ε_t denotes the regression error and $f_Z(Z_{t-1})$ denotes the marginal density function of Z_{t-1}. Thus, the causality-in-quantiles test depends on the regression error ε_t. The regression error ε_t arises based on the null hypothesis specified in equation (3), which holds true if and only if $E[\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})|Z_{t-1}\}] = \theta$. To make the regression error explicit, we rewrite this last statement as $\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is an indicator function. Following Jeong et al. (2012) and based on the regression error, the distance metric can be characterized as:

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

Under conditions (3) and (4), the distance metric in (5) satisfies $J \geq 0$. The statement holds true with an equality, i.e., $J = 0$, if and only if the null hypothesis H_0 in equation (3) is true, while $J > 0$ holds true under the alternative hypothesis H_1 in equation (4). The feasible counterpart of the distance measure J in equation (5) gives us a kernel-based causality-in-quantiles test for the fixed quantile θ and is characterized as:

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

where $K(\cdot)$ represents a known kernel function, h is the bandwidth for the kernel estimation, T indicates the sample size, and p denotes the lag order used to define vector Z_t. Jeong et al. (2012) show that the re-scaled statistic $Th^p\hat{J}_T/\hat{\sigma}_0$ is asymptotically distributed as a standard normal distribution, where $\hat{\sigma}_0 = \sqrt{2}\theta(1 - \theta)\sqrt{1/(T(T-1)h^{2p})}\sqrt{\sum_{t \neq s} K^2((Z_{t-1} - Z_{s-1})/h)}$. The most critical component of the test statistic $\hat{J}_T$ is the regression error $\hat{\varepsilon}_t$. In our specific case, the estimator of the unknown regression error is characterized as:

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

In equation (7), the quantile estimator $\hat{Q}_\theta(Y_{t-1})$ yields an estimate of the θ^{th} conditional quantile of y_t given Y_{t-1}. We evaluate $\hat{Q}_\theta(Y_{t-1})$ by utilising the nonparametric kernel approach:

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

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

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

(9)

In this equation, $L(\cdot)$ signifies a known kernel function and h is the bandwidth utilised in the kernel estimation. The causality in variance suggests an impact on the volatility, which may exist even when there is no causality in the mean (1st moment). Testing for Granger causality in second or higher moments has some complications, and the procedure for such tests should be carefully defined since rejection of causality in the moment m does not imply non-causality in the moment k for $m < k$. We begin by employing Nishiyama et al.'s (2011) nonparametric Granger quantile causality method. To demonstrate the causality in higher-order moments, we first consider the process:

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

where ε_t denotes an independently and identically distributed (i.i.d.) process and the unknown functions $\sigma(\cdot)$ and $g(\cdot)$ satisfy some properties that are sufficient for the stationarity of y_t. Although this representation does not permit linear or non-linear causalities from X_{t-1} to y_t, it does allow X_{t-1} to have predictive power for y_t^2 when $\sigma(\cdot)$ is an established nonlinear function. The representation in equation (10) illustrates that squares for X_{t-1} are not necessarily entered into the nonlinear function $\sigma(\cdot)$. Therefore, we re-specify equations (3) and (4) into a null hypothesis H_0 and an alternative hypothesis H_1 for causality in variance as follows:

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

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

To obtain a feasible test statistic to test the null hypothesis H_0 in equation (11), we substitute y_t in equations (6) to (9) with y_t^2. A problem may arise with the causality test based on the definition given in equation (10), as there may be causality in the second moment (variance) along with causality in the conditional first moment (mean). We can illustrate this with the following model:

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

Thus, higher-order causality in quantiles can be stated as:

$$H_0:\ P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \quad \text{for } k = 1,2,\dots,K \tag{14}$$

$$H_1:\ P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \quad \text{for } k = 1,2,\dots,K \tag{15}$$

Fully incorporating the concepts, we specify that x_t Granger-causes y_t in quantile θ up to the K^{th} moment utilising equation (14) to formulate the test statistic of equation (6) for each k. Nishiyama et al. (2011) construct nonparametric Granger causality tests using the density-weighted approach as in Jeong et al. (2012) and show that density-weighted nonparametric tests in higher moments have the same asymptotic normal distribution as the test for causality in the first moment, although some stronger moment conditions might be necessary.

Nevertheless, it is not an easy task to test for all $k = 1,2, \dots, K$ jointly, as the statistics are correlated (Nishiyama et al., 2011). To overcome this issue, one can follow the sequential testing approach in Nishiyama et al. (2011) to test for causality in both models defined in equations (10) and (13). In this approach, we first test for nonparametric Granger causality in the first moment ($k = 1$) but still continue to test for causality in variance even if non-causality is not rejected. That is, if the null hypothesis for $k = 1$ is not rejected, then there might still be causality in the second moment, and thus, we conduct the tests for $k = 2$. This methodology permits us to test for the presence of causality in variance only as well as causality in the mean and the variance successively. That is, we can examine the existence of causality in mean and causality in variance sequentially. The empirical analysis of nonparametric causality in quantiles requires three specifications: the lag order p, the bandwidth h, and the kernel type for $K(\cdot)$ and $L(\cdot)$ in equations (6) and (9), respectively. In this study, we use the lag order of 1 based on the Schwarz information criterion (SIC) under a VAR involving inflation and gold returns. Additionally, in regard to choosing lags, the SIC is considered to be more parsimonious than other lag-length selection criteria. The SIC helps to overcome the issue of over-parameterization which usually arises in nonparametric frameworks.[2] The bandwidth value is chosen by employing least-squares cross-validation techniques.[3] Finally, for $K(\cdot)$ and $L(\cdot)$, Gaussian-type kernels are used.

3. Data and Empirical Findings

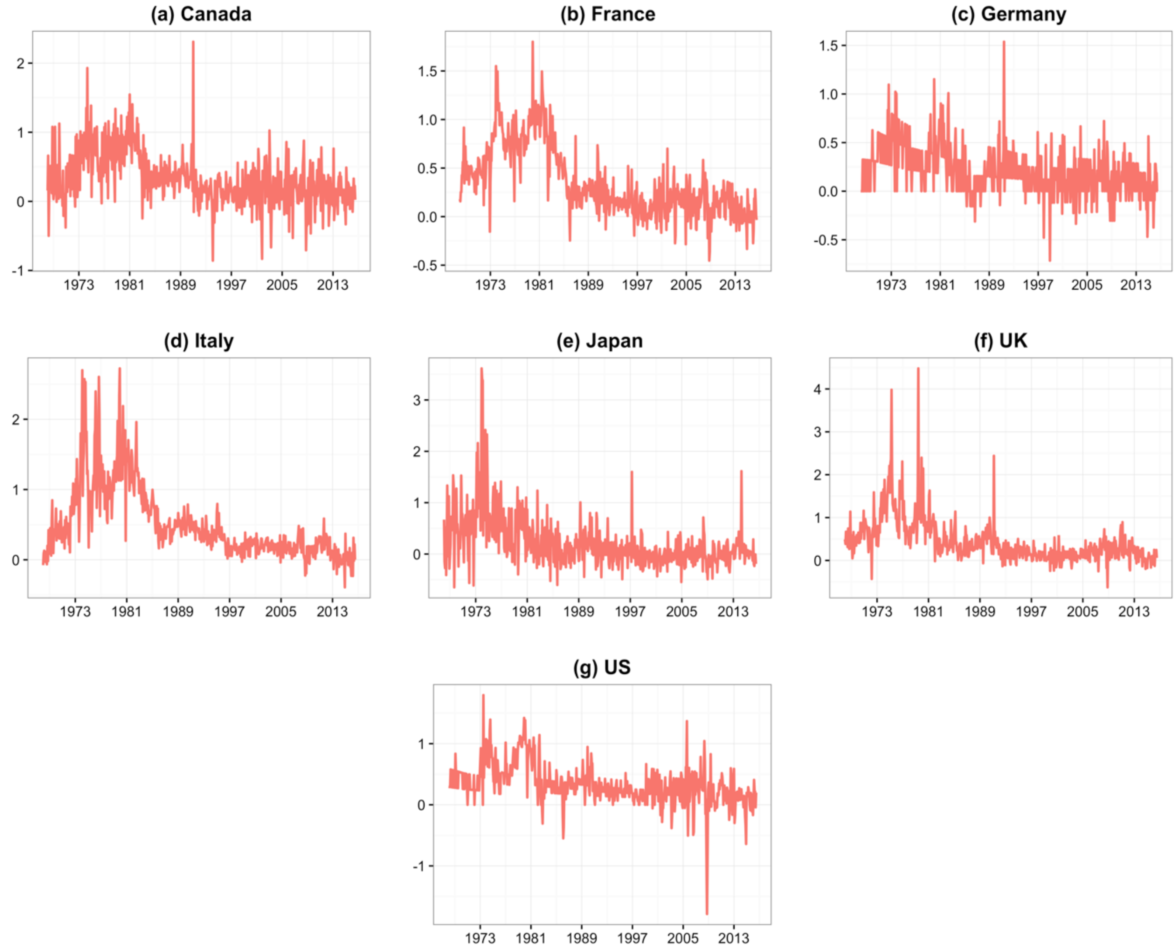
In the empirical analysis, we use the monthly US dollar prices of gold spot and futures contracts traded on the London Bullion Market (LBMA) and the seasonally adjusted Consumer Price Index (CPI) as proxies for price level. Note that the gold future variables represent the gold futures markets at twelve maturities (1-month, 2-month, 3-month, 4-month, 5-month, 6-month, 7-month, 8-month, 9-month, 10-month, 11-month and 12-month). The CPI data is used in monthly frequencies for the period of December 1979-August 2016 period. The CPI series are taken from International Financial Statistics (IFS). Inflation is measured by the monthly difference in the log CPI [$100*\log(CPI_t/CPI_{t-1})$]. Inflation series are stationary, while gold spot and futures price series are non-stationary in log levels, as indicated by

[2] Hurvich and Tsai (1989) examine the Akaike Information Criterion (AIC) and show that it is biased towards selecting an over-parameterized model, while the SIC is asymptotically consistent.

[3] For each quantile, we determine the bandwidth h using the leave-one-out least-squares cross-validation method of Racine and Li (2004) and Li and Racine (2004).

standard unit root tests[4]. Since the methodology requires stationary data, we use gold market returns series and obtain the first differences of the natural logarithmic values of the gold price expressed as percentages. Figure 1 shows the time series plot of the inflation series of G7 countries, while Figure 2 plots the log returns (%) of the spot and futures of the gold spot and futures price series.

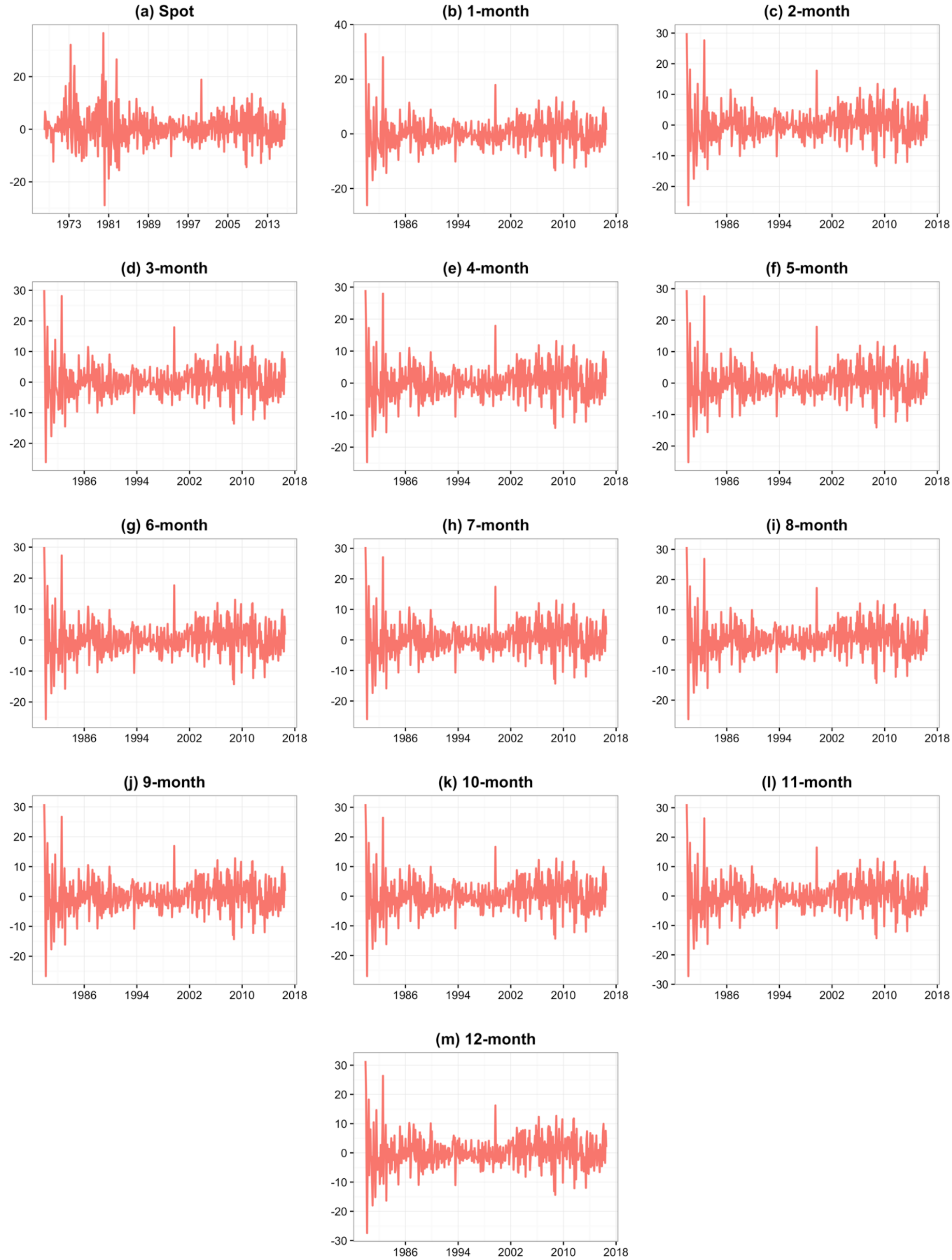
Figure 1. Time series plots of inflation rates



Note: The figure plots monthly inflation rates in percentages.

[4] Complete details of the unit root tests are available from the authors upon request.

Figure 2. Time series plots of spot and futures gold market returns



Note: The figure plots the log returns (%) of the gold markets.

We begin with a brief discussion of selected key features of the series. In Table 1, we report the mean, standard deviation, kurtosis, skewness, Jarque-Bera normality test (JB), Ljung-Box first [Q(1)] and fourth [Q(4)] autocorrelation tests, and first- [ARCH(1)] and fourth-order [ARCH(4)] Lagrange multiplier (LM) tests for autoregressive conditional heteroskedasticity (ARCH) for the inflation series of G7 countries and gold spot and futures contracts. The mean of the inflation series suggests that it is lowest for Germany but gradually increases for Italy. The mean of the gold market returns suggests that it is approximately 0.24. Second, we observe that the inflation series are less volatile than gold market returns. The positive values of the skewness statistic suggest a smaller probability of increases in inflation and gold market returns. All series distributions have fat tails, in accordance with the high values of the kurtosis statistics. More importantly, for our context of causality in quantiles, both variables are skewed to the right with excess kurtosis, resulting in non-normal distributions, as indicated by the strong rejection of the Jarque-Bera statistic at a 1% significance level. The heavy tails of the distributions in both series provide preliminary justification for the nonparametric causality-in-quantiles test used in this paper. The Ljung-Box tests indicate the existence of a first-order serial correlation in the inflation series of G7 countries, while there is no first-order serial correlation in the gold market returns. However, the Ljung-Box tests do not refute the nonexistence of a fifth-order serial correlation in the inflation series and the gold market returns. The autoregressive conditional heteroskedasticity-Lagrange multiplier (ARCH-LM) statistic suggests that ARCH effects exist in all series.

Table 1. Descriptive statistics for inflation and gold returns (%)

	n	Mean	S.D.	Min	Max	Skewness	Kurtosis	JB	Q(1)	Q(4)	ARCH(1)	ARCH(4)	Sample Period
Panel A: Inflation													
Canada	582	0.33	0.37	-0.86	2.31	0.67	1.90	132.48***	94.70***	418.46***	3.76*	23.08***	Feb 1968-Aug 2016
France	583	0.35	0.35	-0.45	1.80	0.88	0.41	80.08***	403.48***	1464.58***	234.04***	269.68***	Feb 1968-Aug 2016
Germany	583	0.21	0.25	-0.71	1.54	0.68	2.23	167.32***	67.04***	241.92***	9.84***	15.15***	Feb 1968-Aug 2016
Italy	583	0.51	0.51	-0.39	2.72	1.61	2.92	462.50***	412.13***	1496.03***	195.87***	218.32***	Feb 1968-Aug 2016
Japan	582	0.22	0.49	-0.65	3.61	2.46	10.48	3276.18***	136.11***	452.68***	191.38***	196.14***	Feb 1968-Aug 2016
UK	583	0.44	0.51	-0.63	4.48	2.56	12.00	4171.21***	278.93***	960.55***	44.68***	60.06***	Feb 1968-Aug 2016
US	583	0.33	0.33	-1.79	1.79	0.09	4.36	468.80***	235.01***	565.50***	129.19***	133.33***	Feb 1968-Aug 2016
Panel B: Gold market returns													
Spot	440	0.26	5.47	-26.12	36.86	0.76	6.79	897.92***	0.06	10.23**	8.57***	25.27***	Dec 1979-Aug 2016
1-month	440	0.26	5.41	-26.13	29.98	0.49	4.61	413.44***	0.00	11.71**	19.96***	21.57***	Dec 1979-Aug 2016
2-month	440	0.25	5.42	-26.18	30.08	0.50	4.71	431.82***	0.00	11.44**	18.48***	19.87***	Dec 1979-Aug 2016
3-month	440	0.25	5.45	-24.70	29.06	0.49	4.10	330.28***	0.01	11.75**	26.91***	18.38***	Dec 1979-Aug 2016
4-month	440	0.25	5.48	-25.14	29.57	0.48	4.27	357.16***	0.00	10.50**	24.23***	19.55***	Dec 1979-Aug 2016
5-month	440	0.24	5.47	-25.56	30.03	0.47	4.36	370.75***	0.00	11.99**	25.97***	17.97***	Dec 1979-Aug 2016
6-month	440	0.24	5.48	-25.94	30.42	0.47	4.48	389.50***	0.01	12.23**	25.73***	18.19***	Dec 1979-Aug 2016
7-month	440	0.23	5.50	-26.31	30.79	0.46	4.59	407.48***	0.02	12.43**	25.32***	18.65***	Dec 1979-Aug 2016
8-month	440	0.23	5.51	-26.65	30.95	0.46	4.66	419.41***	0.04	12.73**	25.43***	19.09***	Dec 1979-Aug 2016
9-month	440	0.23	5.52	-26.98	31.11	0.45	4.72	428.45***	0.07	13.04**	25.96***	19.79***	Dec 1979-Aug 2016
10-month	440	0.22	5.53	-27.23	31.27	0.45	4.79	441.77***	0.11	13.28***	26.43***	20.11***	Dec 1979-Aug 2016
11-month	440	0.22	5.55	-27.46	31.44	0.45	4.86	454.12***	0.17	14.07***	27.04***	21.02***	Dec 1979-Aug 2016
12-month	440	0.26	5.47	-26.12	36.86	0.76	6.79	897.92***	0.06	10.23**	8.57***	25.27***	Dec 1979-Aug 2016

Note: The table reports the descriptive statistics for seasonally adjusted monthly inflation rates (%) for the G7 countries and spot and futures (1- to 12-month) returns (%) for the gold markets. Sample periods start at the period given in the last column of the table and end on August 2016 at a monthly frequency with *n* observations for each series. In addition to the mean, standard deviation (S.D.), minimum (min), maximum (max), skewness, and kurtosis statistics, the table reports the Jarque-Bera normality test (JB), Ljung-Box first [Q(1)] and fourth [Q(4)] autocorrelation tests, and first- [ARCH(1)] and fourth-order [ARCH(4)] Lagrange multiplier (LM) tests for the autoregressive conditional heteroskedasticity (ARCH). The asterisks ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

Although our aim is to investigate the causality in quantiles in both the mean and variance from inflation to gold returns, for the sake of completeness, we perform standard linear Granger causality tests using a linear VAR model. The results of the linear Granger causality tests are reported in columns 2 through 8 of Table 2. The resulting *F*-statistic given in columns (2) and (7) of Table 2 for the null hypothesis that inflation does not Granger-cause gold returns is less than 1.4 for Canada and 1.7 for the UK, respectively. The findings from the linear causality test indicate that there is no evidence of predictability from inflation to gold returns, even at a five percent significance level, for Canada and the UK. In column (3) of Table 2, we see that the null hypothesis that inflation does not Granger-cause gold spot returns is rejected for France only. However, the null hypothesis that inflation does not Granger-cause gold futures markets at various maturities (1-month, 2-month, and 3-month) is rejected at a 5% significance level and nine additional maturities (4-month, 5-month, 6-month, 9-month, 10-month, 11-month, and 12-month) at a 10% significance level. Linear Granger causality results for France indicate that inflation has predictive power for gold futures market returns, with the exception of the spot market. Similar to the findings for France, the evidence from column (4) in Table 2 for Germany indicate that the null hypothesis that inflation does not have predictive power for gold futures market at all maturities is rejected at the 10% significance level, while the null hypothesis that inflation does not have predictive power for gold spot market returns is not rejected at the 5% significance level. Contrary to the results obtained for France and Germany, the findings reported in Table 2 for Italy, Japan and the US show that the null hypothesis that inflation does not have predictive power for gold spot market returns is not rejected at the 5% significance level for these countries, while the null hypothesis that inflation does not have predictive power for gold spot market returns is rejected at the 1% significance level for Italy and Japan and at the 10% significance level for the US. The evidence shown in Table 2 can be summarized as follows. First, there is uniform and strong evidence at the 5% significance level for the power of inflation to predict gold returns for Canada, Italy, Japan, the UK and the US. Second, there is weak evidence of predictability from inflation to gold for Germany, while the results provide strong evidence of predictability from inflation to gold for France, with the exception of the spot market for both countries.

Table 2. Linear Granger causality tests of the null hypothesis that inflation does not Granger-cause gold returns for each G7 country

Gold market	Canada	France	Germany	Italy	Japan	UK	US
Spot	1.3635	0.6068	0.0418	10.2515***	16.3884***	1.1419	3.6561*
1-month	0.6440	5.2767**	5.2326**	0.7534	0.0290	1.6873	0.2655
2-month	0.6324	3.9849**	5.3823**	0.2689	0.0885	0.7538	0.0777
3-month	0.6146	4.0236**	5.3173**	0.2624	0.0890	0.6821	0.0720
4-month	0.6137	3.7694*	5.4752**	0.1435	0.1107	0.7929	0.0353
5-month	0.5985	3.7883*	5.9056**	0.1745	0.0599	1.0480	0.0360
6-month	0.6472	3.6839*	5.3376**	0.1756	0.0788	0.8026	0.0322
7-month	0.6663	3.6202*	5.2710**	0.1860	0.0634	0.8163	0.0279
8-month	0.6766	3.5313*	5.1322**	0.1959	0.0496	0.8330	0.0249
9-month	0.6932	3.4200*	5.0837**	0.1932	0.0356	0.8407	0.0213
10-month	0.6979	3.3027*	4.9562**	0.1916	0.0259	0.8380	0.0158
11-month	0.7072	3.1956*	4.8813**	0.1857	0.0183	0.8533	0.0124
12-month	0.7187	2.9975*	4.8197**	0.1808	0.0116	0.8592	0.0130

Note: The table reports the F-statistic for the no-Granger-causality restrictions imposed on a linear vector autoregressive (VAR) model under the null hypothesis H_0. The order of the VAR is selected by the Bayesian information criterion (BIC). In the table, ***, **, and * indicate rejection of the null hypothesis of no Granger causality at the 1%, 5%, and 10% significance levels, respectively.

To justify the use of the nonparametric quantile-in-causality approach, we statistically examine the nonlinearity dynamics in the relationship between the inflation and gold return series. We apply the Brock et al. (1996, BDS) test on the residuals of the gold return equation in a VAR(1) model of inflation and gold returns. The results given in Table 3 indicate strong evidence at the highest level of significance for the rejection of the null hypothesis of i.i.d. residuals at various embedded dimensions (*m*). These findings provide strong evidence of nonlinearity in gold returns. Thus, given the nonlinearity detected by the BDS test, the Granger causality tests based on a linear framework are likely to suffer from misspecification. Therefore, the results of the linear Granger causality test cannot be deemed reliable. Given the strong evidence of nonlinearity, we turn our attention to the nonparametric causality-in-quantiles test, which is robust to functional misspecification, as it is a nonparametric (i.e., data-driven) approach.

Table 3. [Brock et al. (1996)] BDS nonlinearity test

Gold Market	*m*=2	*m*=3	*m*=4	*m*=5	*m*=6
			Canada		
Spot	8.0836***	10.5065***	12.6977***	15.6595***	18.8721***
1-month	6.1975***	8.2798***	10.9559***	13.5394***	14.9734***
2-month	5.8825***	7.7882***	10.2361***	12.4313***	13.9021***
3-month	5.7787***	7.4884***	9.6189***	11.4365***	12.9964***
4-month	5.8114***	7.7030***	9.3201***	11.1074***	13.2374***
5-month	4.9929***	6.8735***	8.6422***	10.8534***	13.4207***
6-month	5.2925***	7.0103***	8.8667***	11.0644***	13.6667***
7-month	4.9708***	6.7356***	8.6835***	10.6956***	12.9433***
8-month	4.9924***	6.7382***	8.7529***	11.0350***	13.5324***
9-month	4.6728***	6.5385***	8.7002***	10.7985***	12.9979***
10-month	4.6048***	6.4444***	8.7549***	11.0304***	13.2196***
11-month	4.4476***	6.1970***	8.1991***	10.5433***	12.2424***
12-month	4.0707***	6.0809***	8.1123***	10.4975***	12.3199***
			France		
Spot	8.3298***	10.9926***	13.4937***	16.6212***	20.4718***
1-month	5.4320***	7.6419***	9.9553***	12.4475***	13.9305***
2-month	5.4702***	7.5190***	9.5300***	11.7862***	13.4536***
3-month	5.2162***	7.2850***	9.3257***	11.1762***	12.4493***
4-month	5.6760***	7.4833***	9.1383***	11.0351***	12.3833***
5-month	4.9013***	6.8987***	8.9659***	10.8379***	12.6651***
6-month	5.1902***	7.2348***	9.1539***	10.8733***	12.5182***
7-month	5.0249***	7.0332***	9.0641***	10.9055***	12.1858***
8-month	4.7848***	6.9448***	8.9391***	11.0990***	12.4099***
9-month	4.5668***	6.6630***	8.9368***	11.2932***	12.9471***
10-month	4.3260***	6.2412***	8.3188***	10.3793***	12.1480***
11-month	4.0323***	6.0421***	8.0468***	10.2539***	12.2687***
			Germany		
Spot	7.9761***	10.5108***	12.8290***	15.6873***	19.1868***
1-month	6.8318***	9.1409***	11.2467***	13.4961***	15.1028***
2-month	6.4651***	8.6119***	10.5781***	12.5115***	14.2459***
3-month	6.3598***	8.1621***	10.0171***	12.2352***	14.7125***
4-month	6.4040***	8.3843***	10.1910***	11.6455***	13.4460***
5-month	5.7087***	7.7907***	9.7054***	11.5255***	13.6768***
6-month	5.7898***	8.0462***	9.8211***	11.3624***	13.3372***
7-month	5.6663***	7.9580***	9.8827***	11.4297***	13.0755***
8-month	5.4046***	7.6244***	9.6103***	11.3137***	13.1897***
9-month	5.1047***	7.1263***	9.2054***	10.7688***	13.3050***

10-month	4.7911***	6.8609***	8.7956***	10.2797***	12.4558***
11-month	4.5640***	6.6769***	8.5657***	10.0269***	11.7121***
12-month	4.3772***	6.5137***	8.3875***	9.9233***	11.4546***
			Italy		
Spot	7.7253***	9.8736***	12.3246***	15.7227***	19.7286***
1-month	6.4129***	8.5105***	10.7158***	13.2622***	15.1096***
2-month	6.1743***	7.9048***	10.1619***	12.3284***	13.9940***
3-month	5.9442***	7.5319***	9.6356***	11.4473***	12.4579***
4-month	5.8652***	7.5163***	9.1236***	11.0007***	13.3274***
5-month	5.0732***	7.0320***	8.9645***	11.1096***	13.0371***
6-month	5.3783***	7.2362***	9.0764***	11.2165***	12.8696***
7-month	5.2617***	6.9857***	9.0576***	11.0024***	12.8730***
8-month	5.1356***	6.9372***	8.9649***	11.0174***	13.2294***
9-month	4.9222***	6.6279***	8.7792***	10.7791***	13.1932***
10-month	4.8470***	6.4612***	8.5170***	10.5085***	12.4302***
11-month	4.6619***	6.3764***	8.4233***	10.2991***	12.1910***
12-month	4.2294***	6.0705***	8.0221***	9.8652***	11.2196***
			Japan		
Spot	6.8498***	8.8987***	10.9353***	13.9018***	16.8448***
1-month	6.4287***	8.4376***	10.7389***	12.9873***	14.6144***
2-month	5.9545***	8.0622***	10.3745***	12.5752***	15.6516***
3-month	5.6100***	7.4597***	9.7847***	12.0670***	14.2110***
4-month	5.8312***	7.7800***	9.4764***	11.4818***	13.2727***
5-month	4.8679***	6.8164***	8.6668***	10.7947***	12.8730***
6-month	5.2969***	7.2322***	9.0392***	11.0907***	13.1450***
7-month	5.0469***	6.9671***	9.0317***	11.1516***	13.3873***
8-month	5.0610***	7.0447***	9.1742***	11.0815***	12.9707***
9-month	4.7300***	6.6428***	8.9637***	11.1402***	13.4120***
10-month	4.7455***	6.4441***	8.6046***	10.7929***	13.2932***
11-month	4.4347***	6.1937***	8.3213***	10.5489***	12.5651***
12-month	4.2400***	6.1070***	8.0782***	10.2009***	11.7597***
			UK		
Spot	7.7336***	10.4951***	12.8655***	16.0190***	19.7654***
1-month	6.5859***	8.3074***	10.2012***	12.0538***	13.7528***
2-month	6.1401***	7.6873***	9.5142***	11.4746***	13.5932***
3-month	5.9953***	7.5762***	9.4583***	11.3192***	13.4744***
4-month	6.0534***	7.6878***	9.0074***	10.6014***	11.9660***
5-month	5.3932***	7.1299***	8.7506***	10.2304***	11.0223***
6-month	5.4378***	7.0442***	8.4717***	9.9852***	11.1373***
7-month	5.3323***	7.0190***	8.7308***	10.1802***	11.8988***
8-month	5.1973***	6.9048***	8.7179***	10.2776***	11.3407***
9-month	4.9637***	6.6564***	8.4995***	10.0763***	11.1176***
10-month	4.7487***	6.4633***	8.2150***	9.8007***	10.5389***

11-month	4.5948***	6.3607***	8.2939***	10.3098***	11.6561***
12-month	4.3849***	6.2629***	8.1836***	10.2957***	12.4576***
			US		
Spot	8.3255***	10.6854***	13.3487***	17.0143***	20.7251***
1-month	6.4092***	8.5255***	10.9538***	13.7189***	15.9628***
2-month	6.2163***	8.1281***	10.3805***	12.8860***	15.6961***
3-month	5.8329***	7.4664***	9.6421***	11.5647***	13.3464***
4-month	5.8727***	7.8253***	9.3630***	11.6338***	14.3397***
5-month	5.0365***	7.0218***	8.8433***	11.0393***	13.2542***
6-month	5.2591***	7.0063***	8.8782***	11.1851***	13.0522***
7-month	5.2144***	7.0874***	9.0959***	11.1356***	12.9572***
8-month	5.1351***	6.9566***	9.1118***	11.4776***	13.7684***
9-month	4.8989***	6.6872***	8.9497***	11.0861***	13.5248***
10-month	4.7997***	6.5057***	8.6778***	10.8184***	13.0355***
11-month	4.6581***	6.3413***	8.5116***	10.7238***	12.9202***
12-month	8.3255***	10.6854***	13.3487***	17.0143***	20.7251***

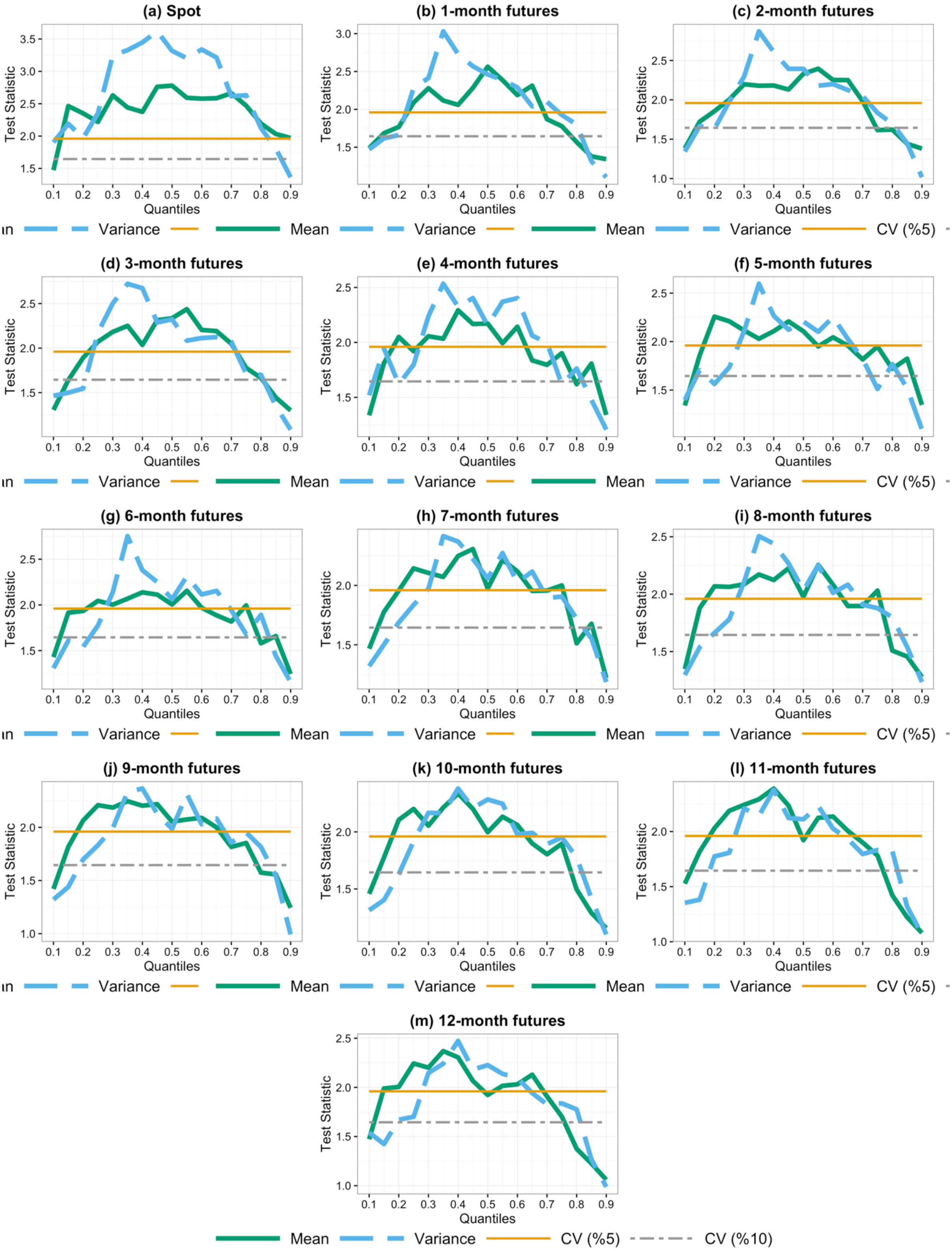
Note: The entries indicate the BDS test based on the residuals of the gold equation in the VAR for various inflation and gold return VAR models. m denotes the embedding dimension of the BDS test. In this table, ***, ** and * indicate rejection of the null hypothesis that residuals are i.i.d. at the 1%, 5%, and 10% significance levels, respectively.

In Figures 3-9, we present the findings of the nonparametric causality-in-quantiles tests for causality from the inflation series to the gold spot and futures price series for Canada, France, Germany, Italy, Japan, the UK and the US, respectively. The figures report the results for both the causality in mean and causality in variance. In each figure, the vertical axis includes the test statistic corresponding to the null hypothesis that inflation does not Granger-cause gold returns, and the horizontal axis includes the quantiles. The 5% critical value is 1.96, and the 10% critical value is 1.64. In these figures, the horizontal, thin, solid lines and the thin, two-dashed lines represent the 5% and 10% critical values, respectively. The findings reported in Figures 3-9 indicate that the results relating to causality in variance have some clear differences from the results for the causality in mean. The evidence in Figure 3 indicates that there is causality in mean and variance from inflation to gold market returns for Canada around the quantile ranges from 0.25 to 0.70. This result indicates that inflation has predictive power for gold returns in Canada. The results for Germany, Italy, Japan and the UK reported in Figures 5, 6, 7 and 8, respectively, are analogous to the findings for Canada. Thus, the evidence from Figures 5-8 shows that the null hypothesis that inflation has no predictive power for gold returns is rejected at the five percent significance level around the quantile range of 0.25 to 0.70, with the exceptions of the lower or upper quantiles for

Germany, Italy, Japan and the UK. This finding indicates that inflation has strong predictive power for gold returns.

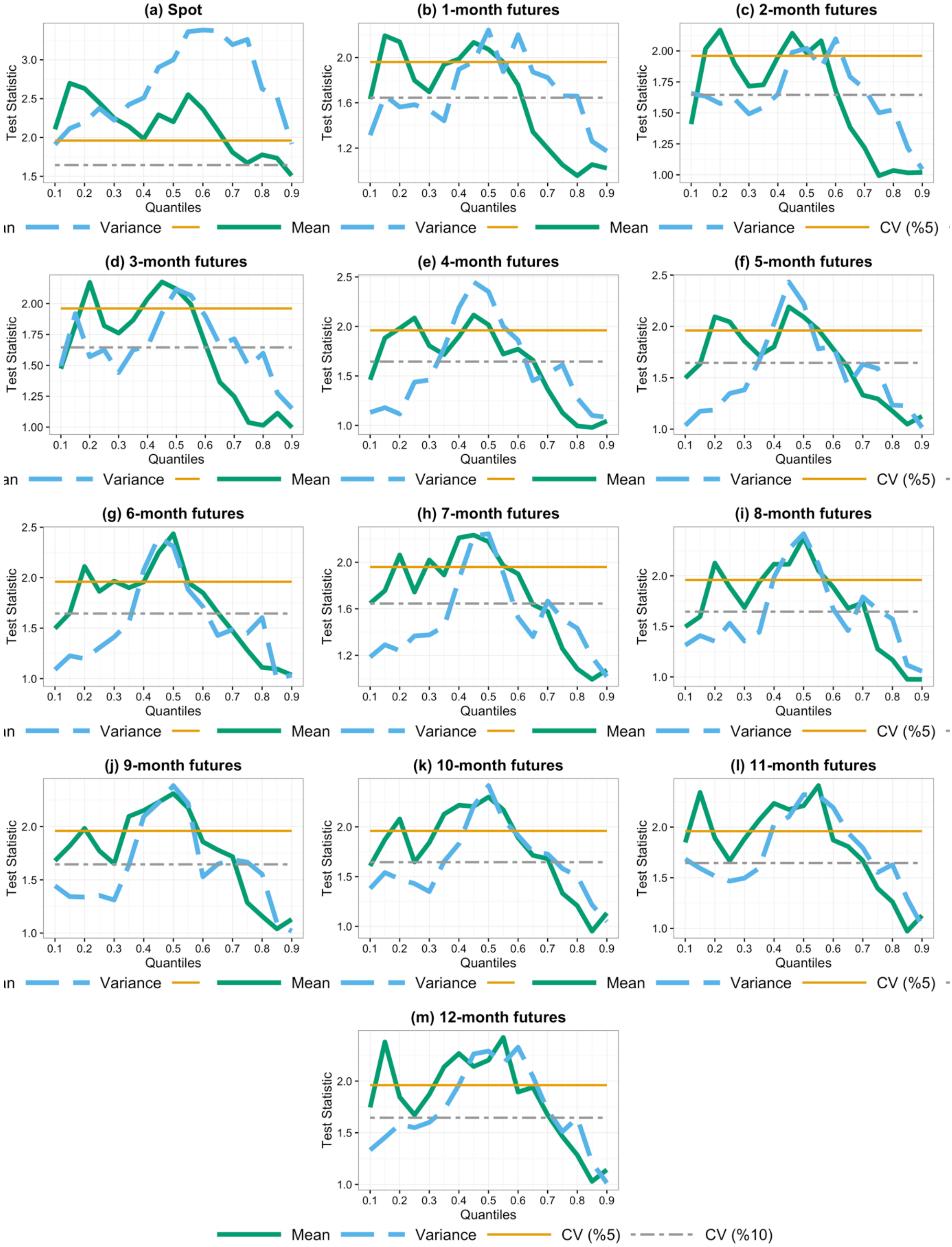
For France, the results in Figure 4 indicate that the null hypothesis that inflation does not Granger-cause mean gold returns is rejected over the quantile range of 0.10 to 0.90, while the null hypothesis that inflation does not Granger-cause gold returns in variance is rejected over the quantile range of 0.10 to 0.65 for the gold spot market. These findings show that there is strong evidence of predictability from inflation to gold returns for the gold spot market. Contrary to the results for the gold spot market case for France, the findings from futures markets at all maturities show that there is weak evidence against the null hypothesis that inflation does not Granger-cause the mean and variance in gold returns. These estimates reveal weak evidence that inflation Granger-causes the mean and variance in gold returns for gold futures markets at all maturities for France. The results for the US reported in Figure 9 are analogous to the results for France.

Figure 3. Causality in mean and variance from inflation to the gold market series for Canada



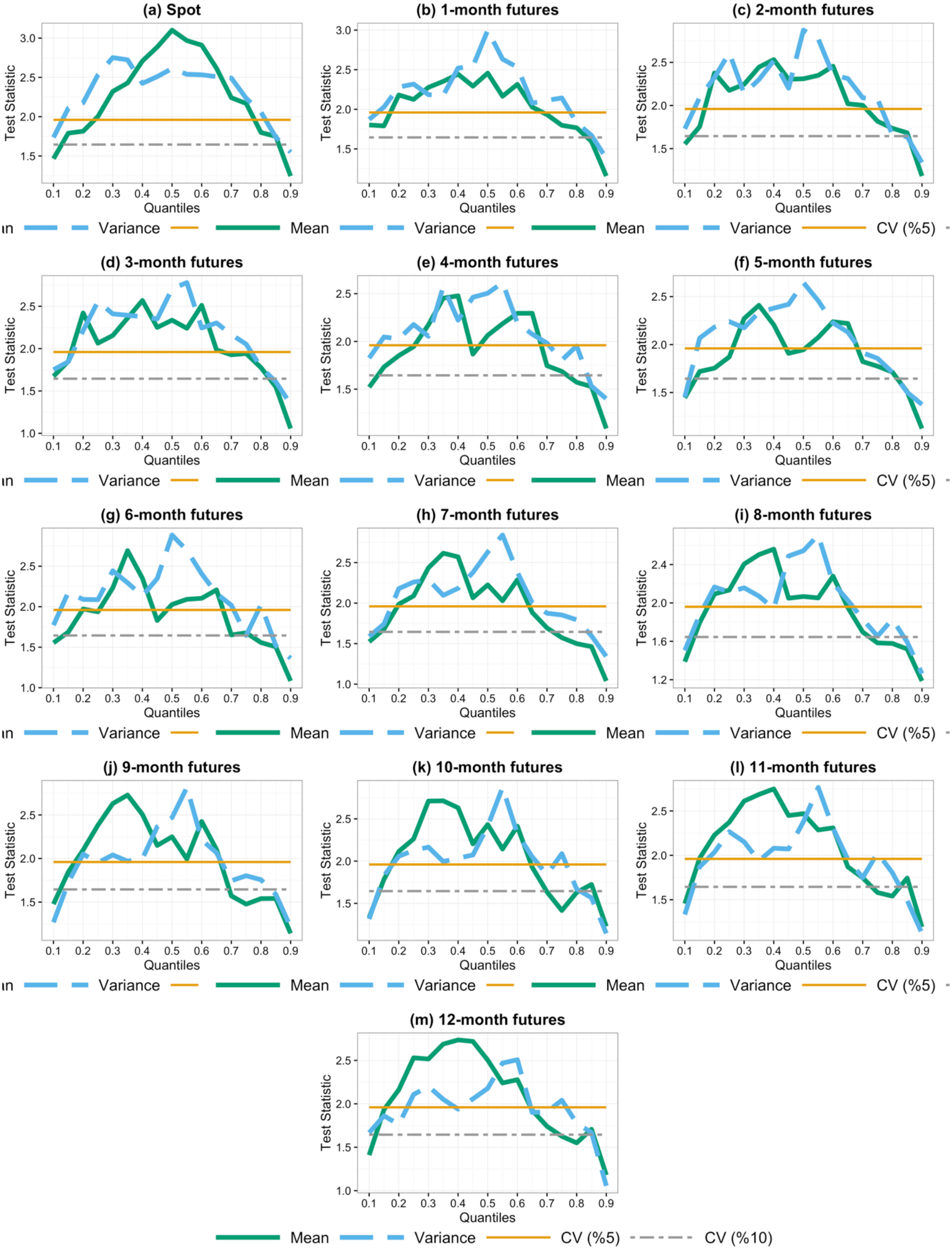
Note: Plots of the estimates of nonparametric causality tests at various quantiles. The horizontal, thin, solid lines and the thin, two-dashed lines represent the 5% and 10% critical values, respectively.

Figure 4. Causality in mean and variance from inflation to the gold market series for France



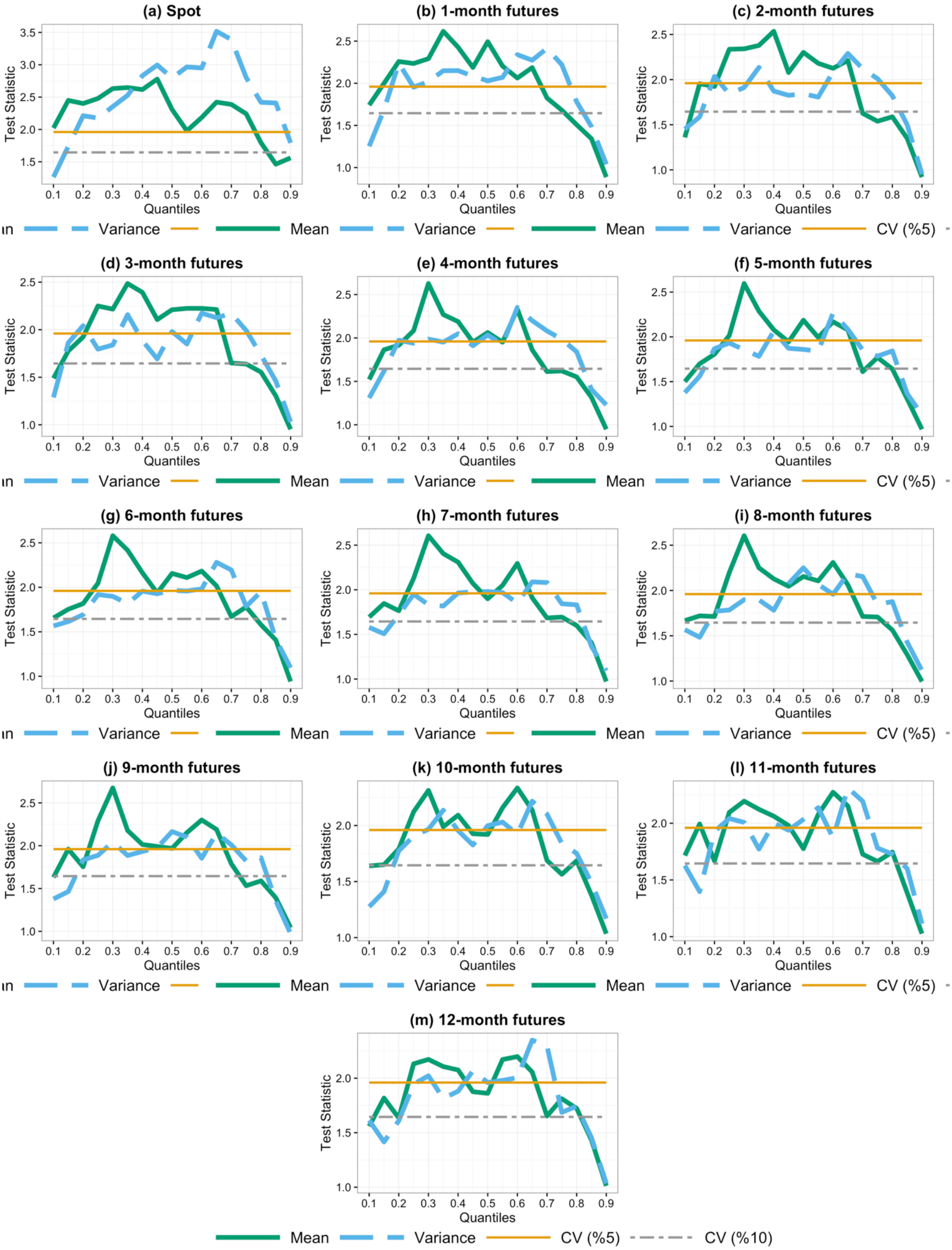
Note: **Note**: Plots of the estimates of nonparametric causality tests at various quantiles. The horizontal, thin, solid lines and the thin, two-dashed lines represent the 5% and 10% critical values, respectively.

Figure 5. Causality in mean and variance from inflation to the gold market series for Germany



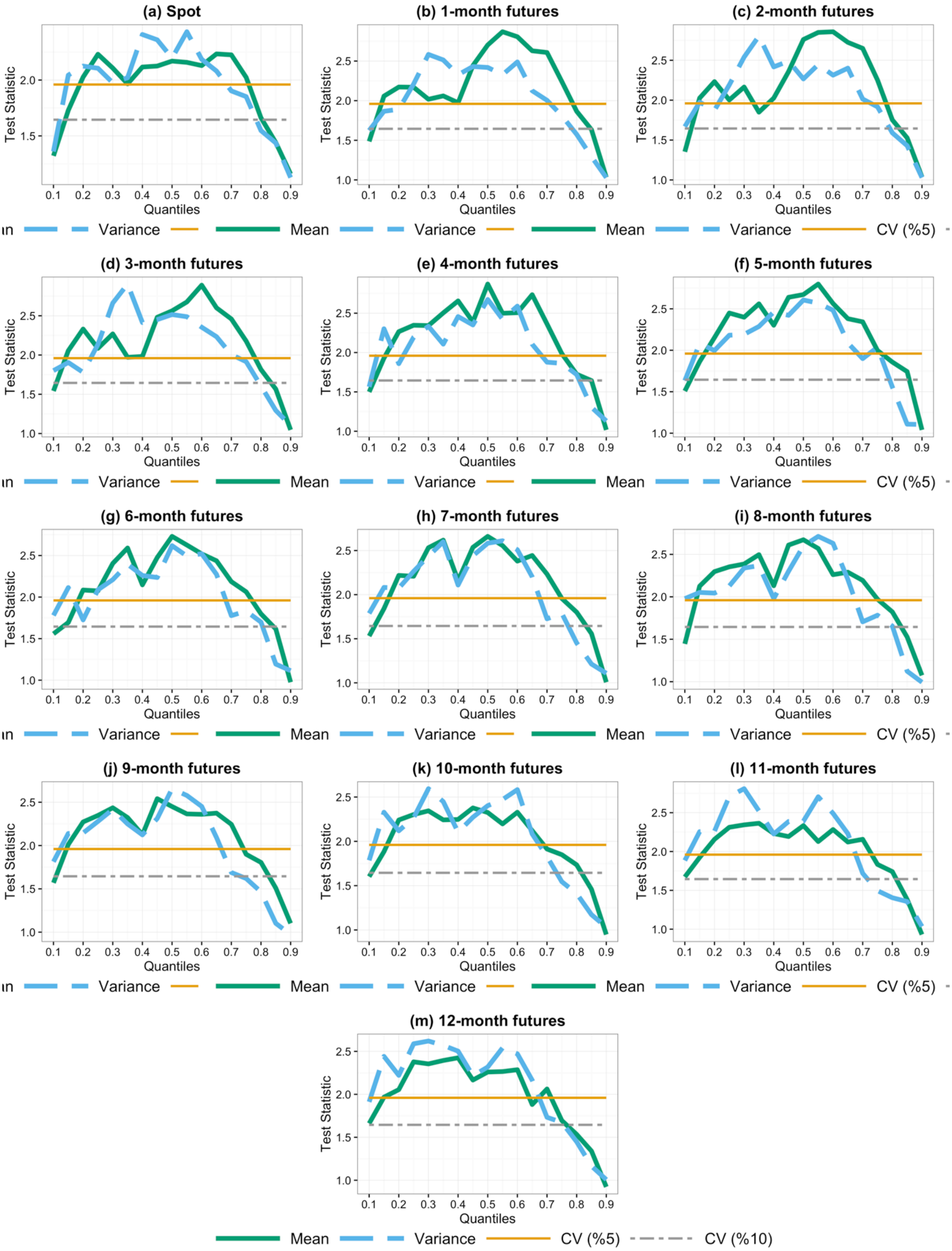
Note: **Note**: Plots of the estimates of nonparametric causality tests at various quantiles. The horizontal, thin, solid lines and the thin, two-dashed lines represent the 5% and 10% critical values, respectively.

Figure 6. Causality in mean and variance from inflation to the gold market series for Italy



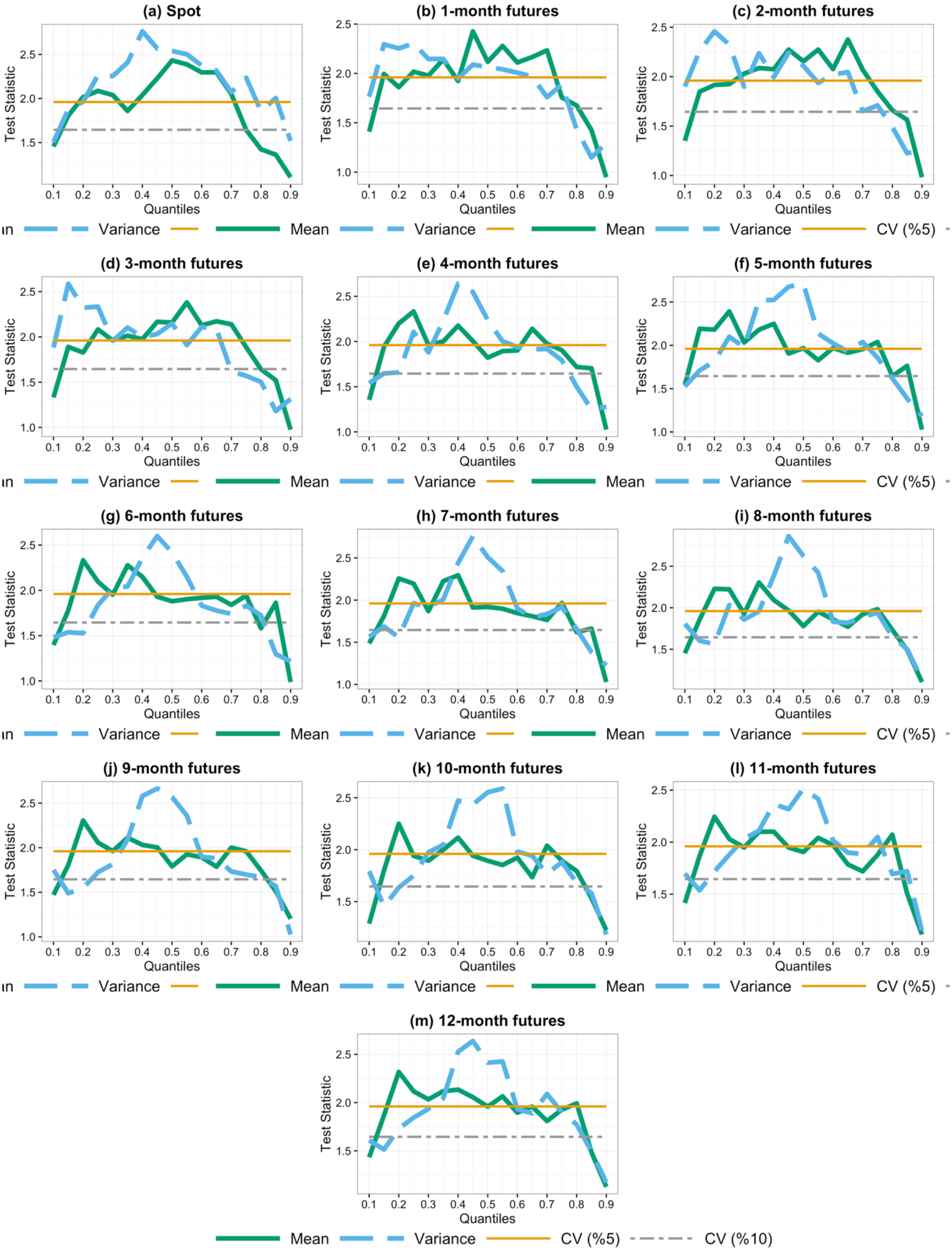
Note: **Note**: Plots of the estimates of nonparametric causality tests at various quantiles. The horizontal, thin, solid lines and the thin, two-dashed lines represent the 5% and 10% critical values, respectively.

Figure 7. Causality in mean and variance from inflation to the gold market series for Japan



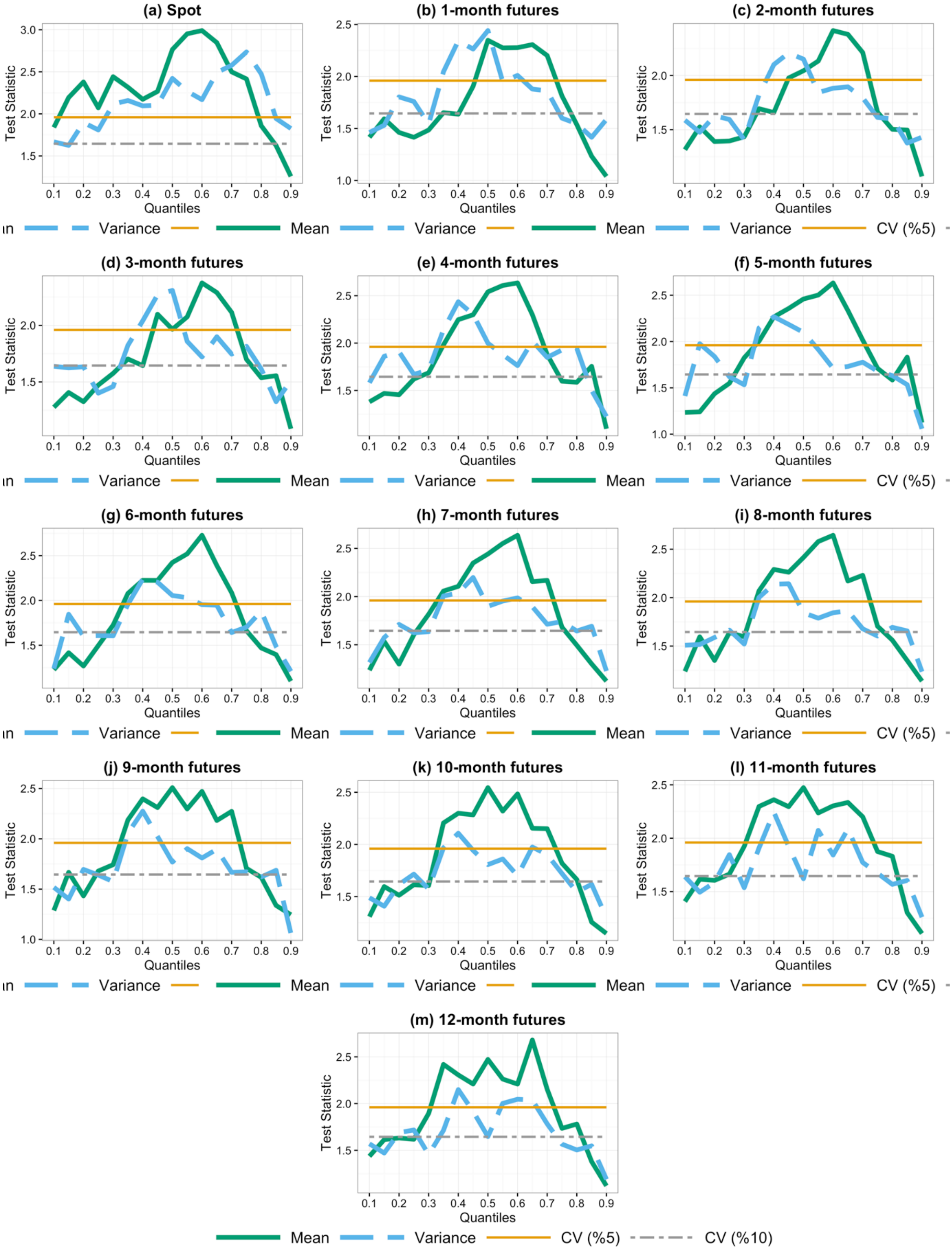
Note: **Note**: Plots of the estimates of nonparametric causality tests at various quantiles. The horizontal, thin, solid lines and the thin, two-dashed lines represent the 5% and 10% critical values, respectively.

Figure 8. Causality in mean and variance from inflation to the gold market series for the UK



Note: **Note**: Plots of the estimates of nonparametric causality tests at various quantiles. The horizontal, thin, solid lines and the thin, two-dashed lines represent the 5% and 10% critical values, respectively.

Figure 9. Causality in mean and variance from inflation to the gold market series for the US



Note: **Note**: Plots of the estimates of nonparametric causality tests at various quantiles. The horizontal, thin, solid lines and the thin, two-dashed lines represent the 5% and 10% critical values, respectively.

The results of causality-in-quantiles tests indicate that inflation has predictive power for gold market returns. This should be the case because inflation and gold market returns are strongly interdependent, as expected. Causality-in-quantiles tests indicate causality from the 0.20 to 0.70 quantile range in most cases. This result leads us to conclude that the changes in low- and high-return ranges in the gold market are not associated with inflation. They may be linked to other factors, such as financial shocks and exchange market shocks. Our findings support the widely regarded idea that gold is a hedge against inflation, but they also show when the hedging role of gold breaks down. Since there is causality in variance as in mean (returns), it is possible to argue that the impact of inflation on gold market volatility may lead to policy uncertainty and consequently increase the cost of policy implementation. It also increases uncertainty among investors and leads to higher risk premiums on gold positions. Our findings may help investors to ensure better asset allocation in inflationary environments. In terms of the continued hoarding of general public investment in gold and large gold reserves held by central banks, the findings of this study suggest that investors should be advised to monitor and be cautious, as their confidence might be eroded by structural changes. The evidence from this study highlights the need to account for nonlinearities when modelling the dynamics of the gold price-inflation relationship. Moreover, the analysis in this study can be extended to gold hedging strategies in inflationary environments.

4. Conclusion

There exists an extensive body of literature investigating the role of inflation in predicting developments in gold markets. We expand upon this literature by investigating the impact of inflation on gold market returns and volatility using a novel nonparametric causality-in-quantiles approach. In the paper, we use monthly data for the sample from December 1979 to August 2016. To assess consistency, we first apply the standard linear Granger causality test. Linear tests might be misleading because they ignore nonlinear dependence and therefore cannot detect causality from inflation to gold returns when nonlinearities exist. The result of the nonlinearity test of Brock et al. (1996) indicates that inflation and gold return series have a strong nonlinear dependence. The evidence of nonlinearity suggests that the linear framework to test causality is in fact misspecified, with unreliable results from these tests. Consequently, we use a novel nonparametric causality-in-quantiles test that combines elements of the test for nonlinear causality of the k^{th} order by Nishiyama et al. (2011) with the causality-in-quantiles test developed by Jeong et al. (2012). The causality-in-quantiles approach allows us to test for causality in both the mean and the variance (volatility). This approach adds additional power to the test when causality in the conditional mean does not exist yet higher-order interdependencies do. Causality-in-quantiles tests find causality from inflation to all spot and futures gold markets, as expected. Intuitively, this should be the case because spot and futures gold markets are highly correlated. Causality-in-quantiles tests usually find causality from quantile 0.20 to quantile 0.70, meaning that very low- and high-return movements in gold markets are not related to inflation. These changes should be related other factors, such as financial shocks and exchange market shocks. We find support that gold serves as a hedge against inflation, a common assumption everywhere in the world. Our findings, however, show that the hedging power of gold does not hold at quantiles lower than 0.20 and higher than 0.70, which corresponds very low- and high-level gold return ranges. Causality is not only in the mean (returns) but also in variance, meaning that inflation has an impact on gold market volatility. In general, our results, via the nexus between inflation and the gold market, highlight the importance of detecting and modelling nonlinearity when analysing predictability via causal relationships.

References

Jaffe, J., 1989. Gold and Gold Stocks as Investments for Institutional Portfolios. Financial Analysts Journal, 45(2), 53–59.

Balcilar, M., Gupta, R., & Pierdzioch, C., 2016a. Does uncertainty move the gold price? New evidence from a nonparametric causality-in-quantiles test. Resources Policy, 49, 74-80.

Balcilar, M., Bekiros, S., & Gupta, R., 2016b. The role of news-based uncertainty indices in predicting oil markets: a hybrid nonparametric quantile causality method. Empirical Economics, forthcoming. DOI: 10.1007/s00181-016-1150-0.

Baur, D., & Lucey, B., 2010. Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold. The Financial Review, 45(2), 217–229.

Beckmann, J., & Czudaj, R., 2013. Gold as an inflation hedge in a time-varying coefficient framework. The North American Journal of Economics and Finance, 24, 208-222.

Blose, L., 2010. Gold prices, cost of carry, and expected inflation. Journal of Economics and Business, 62(1), 35-47.

Brock, W., Dechert, D., Scheinkman, J., LeBaron, B., 1996. A test for independence based on the correlation dimension. Econometric Reviews, 15 197–235.

Chang , H.-F., Huang , L.-C., & Chin , M.-C., 2013. Interactive relationships between crude oil prices, gold prices, and the NT–US dollar exchange rate—A Taiwan study. Energy Policy, 63, 441–448.

Dempster , N., & Artigas, J., 2009. Gold as a tactical inflation hedge and long-term strategic asset. London: World Gold Council.

Ghosh, D., Levin, E., MacMillan, P., & Wright, R., 2004. Gold as an inflation hedge? Studies in Economics and Finance, 22(1), 1-25.

Ghosh, S., 2011. Examining crude oil price – Exchange rate nexus for India during the period of extreme oil price volatility. Applied Energy, 88(5), 1886–1889.

Godness, C., Tsangyao, C., & Gupta, R., 2016. Is gold an inflation-hedge? Evidence from an interrupted Markov-switching cointegration model. Resources Policy, 48, 77-84.

Hurvich, C.M. and Tsai, C.-L., 1989. Regression and Time Series Model Selection in Small Samples. Biometrika, 76, 297-307.

Jeong, K., Härdle, W. K. and Song, S., 2012. A consistent nonparametric test for causality in quantile. Econometric Theory 28, 861-887.

Li, Q. and Racine, J.S., 2004. Cross-validated local linear nonparametric regression. Statistica Sinica, 14, 485-512.

Mahdavi , S., & 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(5), 475–489.

Narayan, P., Narayan, S., & Zheng, X., 2010. Gold and oil futures markets: Are markets efficient? Applied Energy, 87, 3299–3303.

Natanelov , V., Alam , M., McKenzie , A., & Van Huylenbroeck , G., 2011. Is there co-movement of agricultural commodities futures prices and crude oil? Energy Policy, 39(9), 4971–4984.

Nishiyama, Y., Hitomi, K., Kawasaki, Y., and Jeong, K., 2011. A consistent nonparametric Test for nonlinear causality - specification in time series regression. Journal of Econometrics 165, 112-127.

Racine, J.S. and Li, Q., 2004. Nonparametric estimation of regression functions with both categorical and continuous data. Journal of Econometrics, 119, 99-130.

Ranson, D., 2005. Why gold, not oil, is the superior predictor of inflation. London: World Gold Council.

Reboredo, J., 2013. Is gold a hedge or safe haven against oil price movements? Resources Policy, 38, 130-137.

Soytas, U., Sari, R., Hammoudeh , S., & Hacıhasanoglu, E., 2009. World oil prices, precious metal prices and macroeconomy in Turkey. Energy Policy, 37(12), 5557–5566.

Tiwari , A., & Sahadudheen , I., 2015. Understanding the nexus between oil and gold. Resources Policy, 46, 85-91.

Wanga, K.-M., Lee, Y.-M., & Thi, T.-B. (2011). Time and place where gold acts as an inflation hedge: An application of long-run and short-run threshold model. Economic Modelling, 28(3), 806–819.

Worthington, A., & Pahlavani, M., 2007. Gold investment as an inflationary hedge: cointegration evidence with allowance for endogenous structural breaks. Applied Financial Economics Letters, 3(4), 259-262.

Zhang, Y.-J., & Wei, Y.-M., 2010. The crude oil market and the gold market: Evidence for cointegration, causality and price discovery. Resources Policy(35), 168-177.