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Is the price of gold to gold mining stocks asymmetric?

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ABSTRACT

If an asymmetric relation exists between the prices of gold and gold mining stocks, then these firms possess real option characteristics, and therefore, a premium should be added to their valuation. This article examines this proposition, by firstly, using quantile regressions, which are ideally suited to examine asymmetries, and secondly, by accounting for endogenously determined structural breaks in the data. Our findings provide no support for an asymmetric relation. Furthermore, we also show that out-of-sample forecasting shows there is no causality from the gold price to the prices of those gold mining shares used in the sample.

1. Introduction

Under a flexible production model, gold mining firms should hold embedded real option characteristics, which increase their value. This proposition was originally suggested by Brennan and Schwartz (1985), and subsequently supported in empirical work initially by Blose and Shieh (1995) and Tufano (1998) amongst many others. If real option characteristics are indeed important for gold mining firms, then an asymmetric relation should be detected between share prices of these firms and the price of gold. This is due to management increasing production as the gold price increases, specifically when the price is greater than the marginal production cost, while decreasing production when the gold price declines. O'Connor et al. (2016) also show that these real options enable gold mining firms to adjust production costs conditional on the gold price, which in turn is consistent with production costs following gold prices.

Historically, investors have been attracted to gold mining firms since they provide a leveraged investment opportunity to the total expected future production of the gold mine. Thus, the gold exposure coefficients of gold mining shares, or gold "betas", tend to be greater than one, as initially found by Tufano (1998). One key contribution of this paper is that we provide evidence on whether these dynamics have been affected in the era of U.S. Exchange Traded Funds (ETFs), which provide an alternate method for investors to take leveraged positions on gold. In particular over the previous decade financial markets have witnessed an increase in popularity of physically backed gold ETFs, with the SPDR Gold Trust (GLD)[1] now the largest gold ETFs traded globally.[2]

We argue that the introduction and subsequent success of the GLD may have impacted the relation between the price of gold and gold mining company shares. That is in the period before the GLD, gold mining shares provided the primary vehicle for investors to be exposed to the price of gold. However, a share of the GLD represents 1/10 of an ounce of gold and is traded each day like a stock. Hence, owning this financial instrument erodes the need to own gold mining stocks when the primary purpose is exposure to the gold market. It is noteworthy that Baur (2014) also considers this hypothesis and tests it in the Australian context.[3]

Our second contribution stems from the fact that we explicitly account for structural breaks in the relation between the variables using the method developed by Bai and Perron (1998, 2003). Structural breaks are expected in our analysis given the sample period spans the global financial crisis of 2007–2009, as well as a significant run up and then, decline in the price of gold. The primary advantage of

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[1] SPDR funds are a family of exchange-traded funds (ETFs) traded in the United States, Europe, and Asia-Pacific and managed by State Street Global Advisors (SSGA). Informally, they are also known as Spyders or Spiders. SPDR is a trademark of Standard and Poor's Financial Services LLC, a subsidiary of McGraw Hill Financial. Also see Białkowski et al. (2015) investigation of the gold price during crisis and their discussion of Gold ETFs.

[2] As of July 31, 2015, the trust had 21,628,064 ounces of vaulted gold in its custody, representing an asset value of $23,747,009,589. SPDR Gold Shares is one of the top ten largest holders of gold in the world. See http://www.spdrgoldshares.com/#home.

[3] Similarly, for gold mining firms, there is a liquid ETF, the Market Vectors Gold Miners ETF (GDX), which replicates the NYSE/ARCA gold miners' index and is used in the present study, as discussed further below.

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Table 1
Descriptive Statistics.

	Mean	Standard Deviation	Skewness	Kurtosis
RGDX	−.027	2.762	.129	5.574
RGDL	.024	1.304	−.328	5.642
RSPY	.030	1.337	−.085	13.270
ROIL	−.051	2.136	−.249	2.671

Note: This table provides the summary statistics of the variables in the data set. RGDX, RGDL, RSPY and ROIL denote returns of the ETFS for gold mining stocks, price of gold, the S & P 500 index and the crude oil price. Returns are calculated as log price differences and the sample covers the period between May 22, 2006 and May 29, 2015.

the Bai and Perron method is that structural breaks are endogenously determined and hence, researchers do not have to impose ad hoc break dates. Thus, it is more likely that our analysis will capture these inherent instabilities in the gold price relation. Importantly, it is one of the few papers to apply this technique to the precious metals literature.

Thirdly, we utilize quantile regressions, in addition to conventional ordinary least squares (OLS), to examine the gold price exposure of gold mining shares. While OLS regressions are useful to specify the conditional mean response of a dependent variable to an independent variable, quantile regressions can help to determine whether there is a relation at the conditional median, or other conditional quantiles. This can be particularly useful for the primary purpose of the present study. If there is indeed an asymmetric relation between the price of gold and gold mining shares, then, as will be explained later, then different coefficient estimates should be obtained at highly negative and highly positive quantiles of the distribution of the regression coefficient.

Finally, we consider the price of oil as an additional explanatory factor in the analysis. There are several reasons to expect that gold mining stocks should have exposure to the oil price. Gold and oil are both considered strategic commodities as reflected by central bank holdings of physical gold and the strategic oil reserves held by most developed countries (e.g. the Strategic Petroleum Reserve of the U.S. is currently 695 million barrels[4] or US$33.4 billion). Several researchers have also found that the two prices have significant linkages, for example Antonakakis and Kizys (2015), Ewing and Malik (2013), Ciner et al. (2013) and Zhang and Wei (2010). On the other hand, there is also an extensive literature on the impact of oil on the overall stock market, especially stock market volatility (see Kilian and Park (2009), Ciner (2013), Broadstock and Filis (2014), Kang and Ratti (2013), Mensi et al., 2015, Chkili et al. (2014) and Ftiti et al. (2016) as some recent examples), while there are also a number of papers that demonstrate the ability of the oil price to forecast stock returns (see Phan et al., 2015a, 2015b). These papers further motivate the use of oil price changes as a potential risk factor. In addition to contemporaneous relations, we also examine whether there are lagged relations between the risk factors in our model and gold mining shares, which would indicate potential forecasting ability. We therefore investigate the predictive power of the gold price for gold mining shares in an out-of-sample causality analysis.

Our primary findings can be summarized as follows: We show that there are three significant structural breaks in the regression specifying the gold price exposure of gold mining equities. Consistent with prior work, in each of the subperiods, the gold price exposure coefficient is greater than one and statistically significant. However, with regards to the asymmetry in the gold betas, we find no evidence for an asymmetric response in gold mining shares to the price of gold. This finding is contrary to the conclusions of prior work and furthermore, is inconsistent with the view that gold mining stocks have an embedded real option. Hence, it is questionable whether a real option premium should be included in gold mining firm valuations. Finally, there is some evidence to suggest that in the latter part of the sample, the price of gold could be useful to forecast gold mining share returns. As this could be evidence against market efficiency, we also formally investigate causality from gold prices to gold mining shares in an out-of-sample forecasting analysis. Our results suggest no evidence for predictive power consistent with efficiency in these markets.

We organize the rest of the paper as follows: In the next section, we present the data set. In Section 3, we discuss the econometric method and the results of the empirical analysis. We offer the concluding remarks of the paper in the final section.

2. Data

Our data set includes the daily closing (adjusted for dividends) of four ETFs traded on the NYSE/ARCA for the period between May 22, 2006 and May 29, 2015. Note that while GLD ETFs were initially listed on the New York Stock Exchange in November 2004, we begin our sample from May 22, 2006, when other ETFs were also listed, including the key Market Vectors Gold Miners ETF (GDX) on the NYSEArca. The value of this ETF in effect represents in index terms the listed value of the world's leading gold mining firms. The listing of this ETF provides a convenient starting point for our analysis.

We use the GDX for gold mining stock prices, which is a value-weighted average of companies included in the NYSE/ARCA gold mining index. As mentioned above, for the price of gold, we use the GLD and the SPDR Standard & Poor's 500 ETF (SPY) to control for systematic factors that impact the overall stock market. The oil price data are from United States Oil ETF (USO), which replicates the spot price of West Texas Intermediate light, sweet crude oil. We calculate daily returns as $100*\log(P_t/P_{t-1})$ on the series and report summary statistics in Table 1. There is nothing controversial about these statistics, which display some evidence of complexity due to the presence of slight kurtosis and skewness that characterize other financial series, with the mean close to one and time varying volatility.

3. Empirical findings

3.1. Structural breaks

We first construct the following regression model, similar to several papers in prior work such as Baur (2014) as a recent example, to examine the sensitivity of gold mining stocks to gold price movements by controlling for the overall stock market and the price of oil:

$$RGDX_t = a_0 + a_1 RSPY_t + a_2 RGDL_t + a_3 ROIL_t + \varepsilon_t \quad (1)$$

in which *RSPY, ROIL, RGDX* and *RGDL* represent daily returns on the respective ETFs discussed above and *t* denotes the time subscript. Note that a test for cointegration between the variables was undertaken as part of the preliminary investigation, since the presence of cointegration requires the inclusion of an error-correction mechanism in Eq. (1). The full information maximum likelihood method of Johansen and the test statistics, which for brevity are not reported (but are available upon request), point to the somewhat unexpected conclusion that no cointegration is detected between the variables.

With respect to Eq. (1), we expect a_2 to be positive and statistically significant. However, we do not have any *prior* expectation for a_3. An oil price increase could be good news for gold mining stocks as it could indicate greater global economic demand, represented by an increase in retail demand for gold via jewelry purchases. Furthermore, an oil price increase could also be inflationary and it is frequently argued that higher inflation leads to higher gold prices, which again should provide a positive impact. On the other hand, an increase in the oil price could also be bad news for gold mining stocks since it increases energy costs, which are typically very important in this sector. Therefore, we do not form any *ex-ante* expectation for the oil variable.

As mentioned above, an important contribution of the present

[4] See http://www.spr.doe.gov/dir/dir.html.

study is to test for the stability of the above equation and endogenously estimate structural breaks if there is any. If structural changes are not accounted for properly, reliability of estimates will be questionable. We rely on the econometric approach by Bai and Perron (1998, 2003), who develop three different types of statistics to examine structural breaks.

The first is $\mathrm{SupF_T}(k)$ is a supF-type test statistic that tests the null hypothesis of no structural break against the alternative of (k) structural breaks. The second is the double maximum tests (UDmax and WDmax) that test the null of no structural break against the alternative of an unknown number of breaks with an upper limit (k). And the third is $\mathrm{SupF_T}(l+1|l)$ is a sequential test of l breaks against the alternative of l+1 breaks. Based on a Monte Carlo analysis, Bai and Perron (2003) recommend the following approach to utilize these test statistics: First, use the double maximum test statistics to see if at least one break exists and secondly, use the sequential procedure of $\mathrm{SupF_T}(I+1|I)$ to determine the number of breaks.[5] We apply their approach to the model in Eq. (1) and report the results, along with break dates and their 95% confidence intervals, in Table 2.

We find that there exist three structural breaks in the data, and each seems to have intuitive economic appeal: The first one is estimated at October 7, 2008, which is clearly associated with the U.S. subprime crisis and the banking meltdown after the collapse of Lehman Brothers in September of 2008. The second is estimated at February 12, 2010, which signifies the beginning of a spectacular increase in the price of gold from approximately \$1000/oz in February of 2010 to approximately \$1900/oz in August of 2011. And the third break is estimated at June 27, 2013, which coincides with the collapse in the gold price and the subsequent bear market in gold until the end of our sample. Thus, overall it appears the endogenously estimated break dates are fairly reasonable.

Subsequently, we estimate Eq. (1) for each subperiod detected by the structural break analysis and report the results in Table 3. The analysis suggests that gold price betas (a_2) are always positive and statistically significant as expected. The coefficient estimates are also greater than one in each case, which is consistent with the view that gold mining firms represent a leveraged exposure to gold, similar to the results reported in earlier studies. There is, however, time variation in the exposure, as the estimated coefficient in the subperiods range from 1.27 to 2.02. With regards to the question of whether oil price risk is an important factor for gold mining stocks, we only find supportive evidence in only one of the subperiods. It should be mentioned that this is somewhat unexpected since the importance of oil price changes for the stock market is documented in the literature and also, since energy costs are higher than those of average companies for gold mining companies.

3.2. Asymmetry in exposure to the gold price

As argued in the introduction, it is frequently argued that a gold mining firm presents real option like characteristics as it possesses gold reserves that can be tapped if the gold price exceeds a certain cost threshold, i.e. its marginal cost of production. On the other hand, as the gold price declines, production will also decline, since extraction will not be profitable. This suggests that the gold price increases will be more important than gold price declines, since below a certain threshold, further declines should not materially impact the decision making process of the management team (Baur, 2014). One key implication of this view is that gold exposure betas will exhibit asymmetries as they will be larger in higher gold price environments.

The primary goal of our analysis is to determine whether there is reliable statistical evidence for this argument. This is important because researchers, such as Twite (2002), suggest that gold mining

[5] Moya-Martinez et al. (2014) provide a recent application of Bai-Perron tests in an examination of the oil price exposure of Spanish industry equity indices.

Table 2
Bai-Perron structural break tests.

Panel A: GDX				
Test	*p-value*		*Estimated Break Dates*	*Confidence Intervals*
			1st: October 7, 2008	September 5, 2008–November 6, 2008
UDmaxF	83.66	(0.00)	2nd : February 12, 2010	January 14, 2010–March 16, 2010
WDmaxF	106.35	(0.00)	3rd: June 27, 2013	May 20, 2013–August 6, 2013
SupF(2|1)	44.17	(0.00)		
SupF(3|2)	111.29	(0.00)		
SupF(4|3)	15.80	(0.26)		

Note: The results of the Bai-Perron analysis for structural breaks are presented in this table.

Table 3
Gold price exposure estimates.

Coefficients	1st period, t=595	2nd period, t=340	3rd period, t=846	4th period, t=481
a_1	0.66 (0.00)	0.55 (0.00)	0.50 (0.00)	0.63 (0.00)
a_2	1.23 (0.00)	2.00 (0.00)	1.27 (0.00)	2.02 (0.00)
a_3	0.23 (0.00)	0.04 (0.33)	0.04 (0.12)	−0.03 (0.29)
R-squared	0.70	0.76	0.65	0.62

Note: This table presents the OLS estimates of the model in Eq. (1) for each subperiod.

shares trade at a discount and so a real option premium should be added to valuations. If evidence is detected for asymmetry in gold price betas, arguments for this case would be strengthened. The ordinary least squares (OLS) analysis conducted above examines the average (mean) relations between the variables.

However, an asymmetric relation between gold mining shares and the price of gold would suggest that the linkages at the extremes (i.e. very high or low quantiles) should be different than the mean relations. In other words if the asymmetry hypothesis holds highly positive gold mining share returns should be more closely associated with changes in the gold price relative to highly negative gold mining share returns. The quantile regression method, developed by Koenker and Bassett (1978), is ideally suited to test this hypothesis. This is because the quantile regression allows an independent variable to impact a dependent variable at any quantile.

This technique has been used by a number of authors including Ciner (2015), Chuang et al. (2009) and Gebka and Wohar (2013), who demonstrate the potential usefulness of quantile regressions while investigating linkages between returns and trading volume. These papers show that there is Granger causality from trading volume to returns for a set of international equity markets not detected by conventional OLS regressions. Specifically, the studies jointly find that there is positive causality from lagged volume to returns in higher quantiles but negative causality exists from volume to returns at lower quantiles. In addition, Baur and Lucey (2010) examine whether gold acts as a hedge, or safe haven, for stocks and bonds using quantile regression methods. Ciner et al. (2013) later extends the same analysis to include oil and exchange rates along with gold, while Wang and Lee (2016) consider exchange rate relationships.[6]

[6] Note there is also a rich literature that looks at the hedging properties of gold against inflation (e.g. Bampinas and Panagiotidis, 2015), debt and equity markets (e.g. Bredin et al., 2015; Choudhry et al. 2015; Flavin et al., 2014; Poshakwale and Mandal, 2016) and precious metals and precious stones (e.g. Low et al., 2016), oil (e.g. Mensi et al., 2015) to name just a few papers.

Table 4
Quantile regression analysis.

		0.05	0.10	0.90	0.95	Chi-Squared Test
1st period	a_1	0.61 (.00)	0.67 (.00)	0.65 (.00)	0.57 (.00)	0.53 (.91)
	a_2	1.40 (.00)	1.28 (.00)	1.23 (.00)	0.96 (.00)	5.94 (.11)
	a_3	0.24 (.00)	0.23 (.00)	0.28 (.00)	0.35 (.00)	1.35 (.71)
2nd period	a_1	0.60 (.00)	0.49 (.00)	0.60 (.00)	0.70 (.00)	1.67 (.64)
	a_2	2.19 (.00)	1.94 (.00)	2.03 (.00)	1.98 (.00)	5.38 (.14)
	a_3	0.08 (.35)	0.10 (.06)	-0.01 (.88)	0.03 (.78)	1.11 (.77)
3rd period	a_1	0.62 (.00)	0.40 (.00)	0.38 (.00)	0.50 (.00)	5.28 (.15)
	a_2	1.32 (.00)	1.31 (.00)	1.25 (.00)	1.30 (.00)	1.02 (.79)
	a_3	0.03 (.66)	0.10 (.02)	0.05 (.36)	-0.00 (.90)	2.16 (.53)
4th period	a_1	0.83 (.00)	0.71 (.00)	0.56 (.06)	0.42 (.12)	1.89 (.59)
	a_2	1.83 (.00)	1.94 (.00)	2.01 (.00)	1.80 (.00)	3.14 (.37)
	a_3	0.14 (.19)	0.02 (.76)	- 1.2 (.18)	-0.14 (.26)	4.18 (.24)

Note: This table presents the results of quantile regression estimates of the model in Eq. (1) for each specific quantile. The null hypothesis of the chi-squared test is that the estimates are equal across quantiles.

Table 5
Lagged effects.

Quantiles		0.05	0.10	OLS	0.90	0.95	Chi-Squared Test
1st Period	a_1	−0.05 (.83)	0.24 (.31)	0.14 (.12)	0.02 (.44)	0.09 (.49)	4.11 (.25)
	a_2	0.12 (.44)	0.24 (.20)	−0.03 (.65)	−0.25 (.05)	−0.05 (.72)	12.11(.00)
	a_3	0.19 (.03)	−0.12 (.33)	−0.02 (.70)	0.06 (.55)	0.10 (.45)	10.09(.95)
2nd Period	a_1	0.46 (.07)	0.42 (.00)	0.07 (.55)	0.06 (.67)	−0.24 (.18)	2.98 (.39)
	a_2	−0.05 (.88)	0.04 (.85)	0.03 (.83)	0.35 (.10)	0.38 (.16)	1.64 (.65)
	a_3	0.16 (.38)	0.02 (.87)	−0.04 (.64)	−0.26 (.00)	−0.46 (.00)	4.19 (.24)
3rd Period	a_1	0.00 (.98)	0.06 (.79)	0.19 (.00)	−0.02 (.86)	−0.05 (.64)	0.61 (.89)
	a_2	0.32 (.05)	0.32 (.06)	0.96 (.00)	−0.09 (.53)	−0.18 (.36)	9.78 (.02)
	a_3	0.03 (.83)	−0.06 (.63)	−0.12 (.00)	−0.06 (.35)	0.03 (.75)	3.79 (.28)
4th Period	a_1	0.17 (.66)	0.02 (.92)	−0.00 (.99)	0.16 (.63)	0.37 (.38)	0.59 (.89)
	a_2	−0.26 (.36)	−0.39 (.02)	0.24 (.03)	−0.06 (.74)	0.01 (.96)	1.99 (.57)
	a_3	−0.04 (.84)	−0.04 (.65)	−0.10 (.12)	−0.32 (.00)	−0.35 (.01)	2.89 (.40)

Note: This table presents the results of quantile regression estimates of the model in Eq. (1), using lagged values of the explanatory variables, for each subperiod. The null hypothesis of the chi-squared test is that the estimates are equal across quantiles.

The quantile regression analysis is essentially an optimization problem. Koenker and Bassett (1978) show that the coefficients in Eq. (1) can be estimated for any quantile θ ($0<\theta<1$) using linear programming methods, and the simplex method is used in the present paper, with bootstrapped standard errors. It is also noteworthy that the quantile regression is more robust than the OLS to heteroscedasticity and in general non-normal distribution of residuals, which are commonly detected in financial time series. To the best of our knowledge, this is the first paper that applies that quantile regression method to examine the linkage between gold mining shares and the price of gold.

We conduct the minimization procedure at quantiles of θ=0.05, 0.10, 0.90 and 0.95 and obtain quantile specific coefficient estimates. Again, if the asymmetry hypothesis is valid, coefficient estimates for higher and lower quantiles should be different from one another using a chi-square test. The results of the quantile regression analysis can be found in Table 4, again separately for each subperiod. It can be observed that no clear pattern emerges to support an asymmetric relation in higher and lower quantile coefficient estimates, save for the first subperiod. When the asymmetry hypothesis is tested formally by means of a chi-squared test, the null hypothesis of equal coefficients at all quantiles is never rejected. Hence, contrary to the arguments in prior work, we detect no evidence for an asymmetric response of gold mining share returns to gold price movements.

3.3. Lagged effects

In the final part of the empirical analysis, we examine whether lagged effects exist from our explanatory variables to gold mining share prices. This could occur if there is a delayed reaction in the market, which could result in gold prices, for example, forecasting gold mining share returns. We include only one-period lagged values of our explanatory variables, as further lags were never statistically significant, and re-estimate the model in Eq. (1). Again, we conduct the analysis by using both the OLS and quantile regressions to highlight any potential asymmetric in causality relations and the findings are reported in Table 5.

In terms of the OLS analysis, we find no evidence of a lagged impact from any of our explanatory variables to gold mining share returns in the first and second subperiods. However, lagged values of all of our explanatory variables are significant in the third subperiod and moreover, lagged gold prices continue to be statistically significant in the fourth subperiod. This indicates that the gold price could potentially be used to forecast gold mining share prices in the latter part of the sample. This is particularly noteworthy as all of our explanatory variables can be conveniently traded as ETFs. This could potentially be an indication of inefficiency in the market.

In regards to the quantile regression findings, perhaps the most noteworthy result is the link between gold mining shares and the price of oil. We find that in the second and fourth subperiods, the coefficient on lagged oil price is statistically significant, and negative, at the higher quantiles of 0.90 and 0.95. While this finding is not robust across all subperiods, it does indicate that a link exists between gold mining shares and the price of crude oil consistent with arguments raised in the introduction on the potential importance of the oil price for gold mining shares. Specifically, relatively higher gold mining share returns appear to follow declines in crude oil prices in the second and third subperiods. This relation is uncovered only when the quantile regression technique is used, illustrating the importance of this method of analysis. Furthermore, negative causality from oil price to gold mining shares is also consistent with the view that energy costs are highly important for mining companies.

3.4. Out-of-sample forecasting

As the previous section indicates evidence for causality from gold prices to gold mining shares in the latter part of the study, we further examine whether the gold price can improve out-of-sample forecasts of gold mining shares. Out-of-sample analyses tend to suffer less from data mining issues and some researchers, such as Ashley et al. (1980), suggest that reliability of any in-sample causality relation should ultimately be assessed by its out-of-sample predictive ability. Moreover, Chen (2005) finds that when there are structural breaks in the data, an out-of-sample analysis produces more reliable results than an in-sample analysis.

We consider a simple forecasting model as stated below:

$$RGDX_t = a_0 + b_1 RGDL_{t-1} + u_t \quad (2)$$

This equation allows the determination of whether the previous trading day's gold price changes improve one-step-ahead forecasts of gold mining shares. As argued above, lags of gold prices beyond one day are never significant; hence, we include only one lag in the model. The random walk model is the benchmark model used to compare forecasts of our equation. This has been proven to be the hardest benchmark to beat in prior work especially in the exchange rate forecasting literature (e.g. see Chen et al., 2010). The random walk model is also consistent with market efficiency; hence, our analysis also has economic implications in that if our specification in Eq. (2) can generate forecasts that improve predictability over the random walk benchmark, then it is reasonable to argue against market efficiency.

Consistent with the literature, rolling regressions are employed with a fixed window size of 250-observations to calculate out-of-sample forecasts. Rolling regressions tend to be more robust to structural change than recursive regressions. To assess the predictive accuracy of our model relative to the benchmark, we rely on the Clark and West (2007) test, which provides a modification of the well-known Diebold and Mariano test and is robust when the main model and the benchmark model are nested as is our case.[7] The results, however, indicate no predictive ability in gold prices for gold mining stocks over the random walk alternative as the Clark-West test is 0.16 against a critical value of 1.96. Hence, the null hypothesis of no predictive ability for gold prices above the random walk benchmark cannot be rejected. This result is, of course, consistent with efficiency in these markets.

4. Concluding remarks

Prior empirical work argues that gold mining firms possess real option characteristics due to inherent managerial flexibility. If this argument is correct, a premium should be added to the valuation of a gold mining firm. In this study, we reexamine the asymmetry in the relation between gold mining share prices and the price of gold. We utilize a hitherto unconsidered statistical technique in this branch of the literature, quantile regression analysis, which is particularly well suited for the problem at hand. Furthermore, we endogenously identify structural breaks in the relation and finally, utilize data from the ETF era, which importantly has offered investors alternate ways of leveraging gold investments other than through the purchase of gold shares Therefore the analysis does not provide support for the argument that an asymmetric relation exists between the price of gold and gold mining share prices.

A natural implication of our finding is that financial market participants should question the importance –or the value – of adding a real option premium when valuing gold mining firms. We also uncover several lead-lag relations between gold mining shares and the price of gold and the price of crude oil. We show that the lagged gold price tends to have predictive power in the latter part of the sample, which could be the outcome of a delayed response in the market.

In addition, the predictive power of the gold price for gold mining shares in an out-of-sample forecasting exercise is also examined. However, the result of this analysis suggests that in-sample predictive power in some of the subperiods does not translate into improved out-of-sample forecasting power over the random walk benchmark; a finding consistent with market efficiency. Furthermore, as a new finding to the literature, we show that a negative lagged relation exists between the price of crude oil and gold mining shares in two of the subperiods, but only at higher quantiles. In these subperiods, significantly higher gold mining share returns follow crude oil price declines. It would be of interest to examine in future research whether a similar relation exists between the price of oil and other sectors of the stock market.

[7] Details of the Clark-West and Diebold-Mariano tests are discussed in many papers in the literature. Hence, we refrain from further discussing them in the present study. Ashley and Ye (2012) provides a review of several predictive accuracy test statistics.

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