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The Dynamics of Gold Prices, Gold Mining Stock Prices and Stock Market Prices Comovements

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Abstract

We examine the dynamic relationships between gold prices, stock price indices of gold mining companies and broad stock market indices. Evidence of cointegration between these variables is found. A vector error-correction model reveals that both gold and large-cap stock prices adjust to disturbances to restore the long-term relationship between the variables. Short-term unidirectional causal relationships are running from large-cap stock prices to gold mining company stock prices and from gold mining company stock prices to gold prices.

Keywords: Gold mining company stock prices, Cointegration, Vector error-correction model

1. Introduction

The returns of gold-related securities, such as common stock in gold mining companies, are widely considered to be related to changes in gold prices and, to a much lesser extent, to general stock market returns. A number of studies have examined the relationship between gold prices and gold mining company returns, including Blose and Shieh (1995), Sjaastad and Scacciavillani (1996), Tufano (1998), Christie-David et al. (2000), Twite (2002), Faff and Hillier (2004), and Fang et al. (2007). Based on regression analysis, gold mining company stocks were found to have a greater exposure to gold price returns than to stock market returns (gold betas were higher than market betas). It is surprising that little attention has been devoted to investigating the time series characteristics and possibilities of a long-term cointegrating relationship between these variables. In fact, we are aware of only one study that tests for nonstationarity in any of these variables (Smith, 2001). Smith examined the short-term and long-term relationships between four gold price series and six different US stock price indices over the 1991-2001 time period. Smith reported that gold prices and US stock index levels were nonstationary, but were stationary in first differences. He found no bilateral long-term relationship, or cointegration, between a gold price series and a stock market index. There was, however, some evidence of a negative short-term Granger causality running from US stock index returns to gold returns, but not the reverse.

The regression studies cited above show that interrelationships exist involving three types of variables: gold prices, gold mining company stocks, and a broad market index. However, Smith (2001) shows that it is important to take into account the time-varying nature of the data to establish a properly specified model. His approach also does not assume an independent variable but instead allows for the possibility that all the variables are endogenous. The present study expands on these previous findings by examining the dynamic relationships involving all three types of variables. In particular, a multivariate cointegration analysis is developed to establish their short-term and long-term behavior. In this paper, two gold price series (morning and afternoon fixing in London), two gold company stock price indices (GOX and HUI) and three stock market indices representing large, mid and small capitalization stocks are employed. Multivariate cointegration tests are performed to investigate their long-term comovements. Variance decompositions and impulse response functions provide additional information to the long- and short-run dynamics of the series.

Overall, our results show that, in contrast to the bivariate analysis by Smith (2001), our broader multivariate approach does support a long-term equilibrium relationship between gold prices, gold mining company stock prices, and stock market prices. We find that cointegration is present in a model involving the GOX, the three stock market indices, and either morning or afternoon gold price. When there is deviation from the long-term equilibrium, both gold prices and large-cap stock prices (the S&P500) are the leaders in rapidly restoring the relationship. As to the short-term dynamics, our results are similar to Smith (2001) but provide a more interesting picture. We found a negative Granger causality from the large-cap index to the GOX gold mining company stock index and a positive causality from the GOX to gold prices. This indirect linkage between stock market returns and gold returns via GOX may be explained by a preference by investors to move to (from) gold mining stocks, rather than to (from) gold directly, in times of adverse (positive) broad stock market movements. Changes in gold mining company stock prices may then convey information useful to investors in the commodity itself.

The rest of the paper is organized as follows. The data are described in Section 2. Section 3 presents briefly the methodology and reports the empirical results. Section 4 contains the concluding remarks.

2. Data and Descriptive Statistics

We use weekly (Wednesday) data over the period June 5, 1996, through January 31, 2007, for a total of 557 observations.(Note 1) Gold price series include the London morning fixing (GAM) and the London afternoon fixing (GPM), both in US dollars. Gold mining company stock price series are represented by two indexes. The first, the CBOE Gold Index (GOX), is an equal-dollar weighted index composed of 12 companies involved primarily in gold mining and production with common stocks or ADRs listed on the NYSE, AMEX, or NASDAQ-NMS.(Note 2) The second, the AMEX Gold BUGS (Basket of Unhedged Gold Stocks) Index (HUI), is a modified equal-dollar weighted index of 15 gold mining companies.(Note 3) The S&P 500 (LCAP) index is used to proxy for large company stocks. Since most gold mining firms are not large capitalization companies, the S&P midcap 400 (MCAP) and the S&P smallcap 600 (SCAP) indexes are also included in the analysis. All series are converted to logarithmic form. The returns series are constructed as the first differences of the level series.

Summary statistics for the returns series are shown in Table 1. The three stock market indices have the highest mean returns, while the gold mining stock indices have the highest standard deviations. All of the return series have nonsymmetric distributions. Negative skewness of the gold mining company and stock market indices implies a thicker lower tail (skewed to the left), while returns on gold price series are skewed to the right. The kurtosis statistics indicate that all the returns series are more peaked than a normal distribution. For a normal distribution kurtosis is equal to 3. The Jarque-Bera statistic confirms that none of the series is normally distributed.

Table 1 also reports the average correlation statistics between the weekly returns of each pair of indices studied over the 1996-2007 sample period. Correlations are strong between the gold mining company stock indexes (0.9569), as 11 out of the 12 companies included in the GOX are also part of the HUI, and between AM and PM gold price fixing (0.9439). As expected, gold mining stocks are relatively highly positively correlated with gold and more positively correlated with small capitalization stocks than with medium and large capitalization stocks. Finally, consistent with Smith (2001) results, gold and stock market returns have the lowest correlation coefficients, with the gold series being practically uncorrelated with mid-and small-cap stocks and slightly negatively correlated with large stocks.

3. Methodology and Empirical Results

This study uses the methodology of cointegration, as developed by Johansen (1988) and Johansen and Juselius (1990), henceforth referred to as JJ, to test for the presence of long-run equilibrium relationships between time-series variables (details of the cointegration methodology are discussed in Appendix 1). Cointegration tests provide a means to determine whether a set of endogenous variables (e.g., gold mining company stock prices, gold prices and stock market prices) share a common long-run stochastic trend (have a long-term relationship), while allowing for the possibility of short-run divergences. A finding of cointegration indicates interdependence of the endogenous variables, which may be the result of economic linkages between the markets or arbitrage activity between investors.

Table 1. Summary of statistical properties of weekly index return series

Statistic	Index series						
	GOX	HUI	GAM	GPM	LCAP	MCAP	SCAP
N	556	556	556	556	556	556	556
Mean	0.0003	0.0009	0.0009	0.0009	0.0014	0.0022	0.0019
Median	0.0004	-0.0004	0.0007	0.0009	0.0028	0.0057	0.0049
Maximum	0.2108	0.2127	0.1891	0.1532	0.1018	0.0936	0.1165
Minimum	-0.2200	-0.2138	-0.0455	-0.0844	-0.0904	-0.0857	-0.1226
Stan. dev.	0.0534	0.0533	0.0215	0.0211	0.0230	0.0250	0.0264
Skewness	-0.0550	-0.0455	1.4066	0.4927	-0.0781	-0.1990	-0.3331
Kurtosis	4.0213	4.1712	14.5044	8.7933	4.7682	4.100	4.6056
Jarque-Bera	24.4419	31.9671	3167.6520	802.0302	72.9951	31.6796	70.0025
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Correlation							
GOX	1.0000						
HUI	0.9569	1.0000					
GAM	0.5459	0.5644	1.0000				
GPM	0.5906	0.6120	0.9439	1.0000			
LCAP	0.0747	0.0808	-0.0580	-0.0684	1.0000		
MCAP	0.1449	0.1476	-0.0003	-0.0075	0.9018	1.0000	
SCAP	0.1482	0.1546	0.0191	0.0112	0.8222	0.9414	1.0000

Index returns are estimated as the log-relative of weekly prices for June 5, 1996 to January 31, 2007. GOX: CBOE Gold Index; HUI: AMEX Gold Index. GAM: Gold price, morning fixing at London; GPM: Gold price, afternoon fixing at London. LCAP: S&P 500 Index; MCAP: S&P Midcap 400 Index; SCAP: S&P Smallcap 600 Index.

3.1 Unit Root Tests

Two or more nonstationary time series are cointegrated if a linear combination of the variables is stationary. Therefore, the first step in the analysis is to examine each series for the presence of unit roots, to determine if the index series are nonstationary. Nonstationarity is a precondition for cointegration; additionally, all the series must be integrated of the same order. For this, the Augmented Dickey-Fuller (ADF) and Phillips and Perron (PP) tests are applied to the levels and first differences of each series; the null hypothesis is that a series is nonstationary, so rejection of the unit root hypothesis supports stationarity. The results, using the Schwartz Information Criterion (SIC), are presented in Table 2. For all the level series under study the null hypothesis of a unit root is not rejected. However, when the tests are applied to the first differences of the series, the null is rejected indicating that they are stationary. Consequently all seven level series are integrated of order one, that is, I(1).

3.2 Cointegration Tests

Once the nonstationarity requirements of the level series are met, the Johansen and Julius (1990) procedure can be applied to determine whether the time series are cointegrated. This test determines the rank (r) of the coefficient matrix of a vector autoregression (VAR) model of the series, with the rank indicating whether there is cointegration, as well as the number of cointegrating relationships. Two likelihood ratio tests are used, the trace test and the maximum eigenvalue test, to determine the number of cointegrating vectors. The trace test null hypothesis is that there is a maximum of r cointegrating vectors against the alternative that the number is equal to n, the number of series in the model. That is, the null hypothesis, that $r = 0$, is tested against the alternative hypothesis, $r \geq 1$. If this null is rejected, the null of $r \leq 1$ is tested against the alternative that $r \geq 2$. If this null is rejected, the null becomes ≤ 2, tested against $r \geq 3$, and so on. The maximum eigenvalue test has the identical null hypothesis, while the alternative is r+1 cointegrating vectors.

Table 2. Unit root tests results for weekly indices

Index	Index level		First difference	
	ADF	PP	ADF	PP
GOX	-2.16	-2.01	-23.63*	-24.34*
HUI	-2.05	-2.01	-23.42*	-23.61*
GAM	-1.73	-1.50	-22.16*	-23.12*
GPM	-1.68	-1.47	-22.25*	-23.13*
LCAP	-2.21	-2.18	-25.91*	-25.89*
MCAP	-2.74	-2.73	-24.80*	-24.79*
SCAP	-2.76	-2.89	-24.14*	-24.14*

Unit root tests are conducted using the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) tests. Lag lengths and model were chosen according to the Akaike Information Criterion (AIC). The critical values are based on MacKinnon (1991); an asterisk indicates significant at the 5 percent level. GOX: CBOE Gold Index; HUI: AMEX Gold Index; GAM: Gold price, morning fixing at London; GPM: Gold price, afternoon fixing at London LCAP: S&P 500 Index; MCAP: S&P Midcap 400 Index; SCAP: S&P Smallcap 600 Index.

Before testing our model, we perform bivariate cointegration tests on each gold price series with each stock market index, to see if our selection of series and time period produce the same results as Smith (2001). We find no evidence of cointegration of these variables on a bilateral basis. We also reach the same conclusion for bivariate cointegration tests of each gold mining company stock index with each gold price and with each stock market index. We then proceed to our multivariate model. More specifically, each gold mining company stock price index (GOX or HUI) is tested for cointegration with each gold price series (GAM or GPM) and the three stock market price indices (LCAP, MCAP and SCAP).(Note 4) The estimation for each grouping of five series assumes unrestricted intercepts and no trends. A lag of one is used for each grouping, based on the Akaike Information Criterion (AIC). The cointegration test results are reported in Panel A of Table 3 for the GOX grouping and in Panel B for the HUI grouping.

Table 3. Multilateral cointegration tests results

Panel A. Gold mining company stock prices (GOX), gold prices and stock market prices			
Hypotheses		Trace test	Critical values
Null	Alternative		
r=0	r≥1	94.60*	76.97
r≤1	r≥2	47.55	54.08
r≤2	r≥3	28.75	35.19
r≤3	r≥4	13.20	20.26
r≤4	r≥5	4.67	9.16
		Maximum eigenvalue test	
r=0	r=1	47.05*	34.81
r≤1	r=2	18.81	28.59
r≤2	r=3	15.55	22.30
r≤3	r=4	8.54	15.89
r≤4	r=5	4.67	9.16
Panel B. Gold mining company stock prices (HUI), gold prices and stock market prices			
Hypotheses		Trace test	Critical values
Null	Alternative		
r=0	r≥1	74.05	76.97
r≤1	r≥2	44.41	54.08
r≤2	r≥3	25.57	35.19
r≤3	r≥4	12.97	20.26
r≤4	r≥5	4.65	9.16
		Maximum eigenvalue test	
r=0	r=1	29.64	34.81
r≤1	r=2	18.84	28.59
r≤2	r=3	12.6	22.30
r≤3	r=4	8.32	15.89
r≤4	r=5	4.65	9.16

The results show that the group including the HUI series is not cointegrated: we cannot reject the hypothesis that there are no cointegrating vectors. In contrast, the GOX grouping is cointegrated, as both the trace and the maximum eigenvalue tests reject the null hypothesis of no cointegration, suggesting that there is one significant cointegrating vector in the model. This implies that there are four common stochastic trends, indicating a degree of market integration. Therefore, we conclude that there exists a stationary, long-run relationship between gold mining company stock prices (GOX), gold prices (GAM or GPM) and stock market prices (LCAP, MCAP, and SCAP). It appears that, in contrast to the bivariate gold price and broad stock index model of Smith (2001), the inclusion of the GOX gold mining company stock price index as an additional variable has brought out a force that comoves the system.

The r denotes the maximum number of cointegrating vectors. The 5 percent critical values provided by Osterwald-Lenum (1992) indicate a single cointegrating factor for the GOX grouping but fail to reject the null of no cointegration for the HUI grouping.

In addition to testing for cointegration over the sample period as a whole, we also apply a dynamic procedure to examine the robustness of our findings. A rolling window covering the first half of the data (5 years) is created and the trace statistic is computed. The window is then moved forward one week at a time and the trace statistic is computed for each window to examine temporal changes in the cointegration relationship. A ratio of the calculated to the critical trace statistic is constructed; thus, a ratio exceeding 1.0 constitutes evidence for cointegration. The results are shown in Figure 1a for the GOX grouping and Figure 1b for the HUI grouping. These graphs indicate that for much of the period the GOX grouping is cointegrated, while the HUI grouping indicates cointegration over only a small part of the period. The highest ratios occur starting around October 2004, as the GOX, LCAP and MCAP indices moved sharply higher, followed later by gold prices and the HUI index.

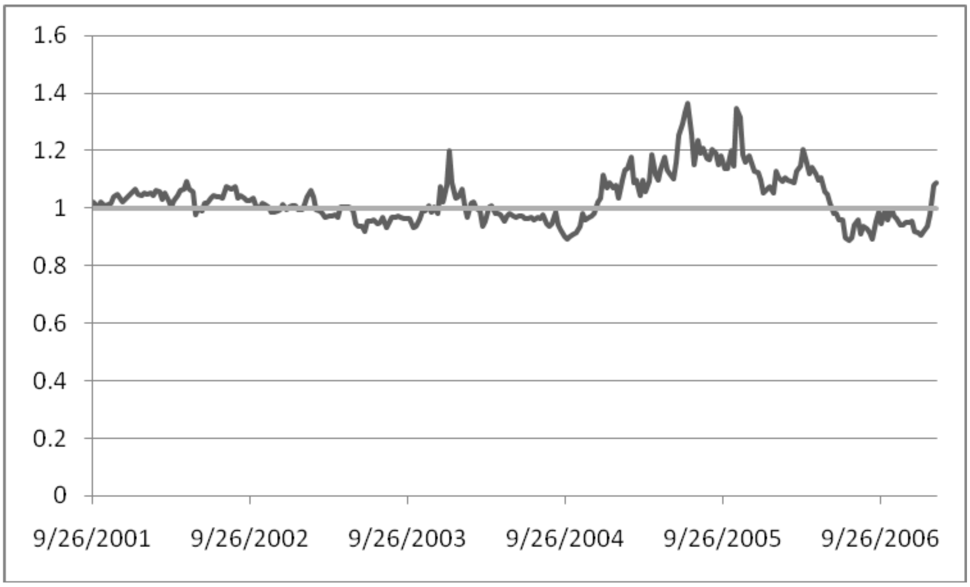

Figure 1a. Rolling Window Trace Statistic for the GOX Grouping

Figure 1b. Rolling Window Trace Statistic for the HUI Grouping

The trace statistic is shown as a ratio of the calculated to the critical value. The results are presented as of the ending date of each rolling window.

3.3 Tests for the Dynamics of the GOX Grouping

Since the evidence indicates cointegration for gold mining company stock (GOX), gold (GAM) and the three stock market indices (LCAP, MCAP and SCAP), the use of an unrestricted vector autocorrelation (VAR) model in first differences would be misspecified as information on the long-term equilibrium relationship is lost. Therefore, the next step is to estimate a Vector Error-Correction (VEC) model. The VEC model results are contained in Table 4.(Note 5)

The significance and size of the coefficients on the cointegrating equation in Table 4 capture the response of each series in the GOX grouping to departures from the long-run equilibrium. The results indicate that the opening gold price index (GAM) and the large capitalization stock price index (LCAP) adjust to disturbances to restore long-range equilibrium, but that the gold mining company stock price index (GOX), the midcap stock price index (MCAP), and the smallcap stock price index (SCAP) do not react significantly. With a larger coefficient, the gold price series adjusts more rapidly to shocks (and in opposite direction) than the large capitalization stock price series. The opposite signs on those two coefficients indicate that a positive long-term adjustment by one variable, say the large capitalization stock price index, will be accompanied by a downward adjustment by the other variable, say the gold price. Short-term interactions are shown by the coefficients on the lagged differenced terms. Contrary to Smith (2001), we do not find a unidirectional or bi-directional Granger causality between gold prices and broad stock market indices. Nevertheless, our results are consistent with his findings based on a VAR model. In our VEC model, which includes a gold mining company stock index, the relationship between gold prices and broad stock market indices is indirect. Instead of (negative) Granger causality between the stock market index and gold prices, there is a unidirectional (negative) Granger causality running from the largecap index (LCAP) to the GOX and a unilateral (positive) Granger causality from the GOX to gold prices (GAM). Thus, the causality observed by Smith (2001) between the stock market index and gold prices appears to run through the gold mining company stock price index. Interestingly, the gold mining company stock price index (GOX) influences the gold price index (GAM), but not the reverse. Overall, the large capitalization stock price index adjustment to long-term disequilibrium is transmitted to the gold mining company stock price index and to gold prices through this short-term process. Both the mid and small capitalization stock price indices (MCAP and SCAP) affect the large capitalization stock price index (LCAP), but there is no Granger causality in the other direction.

Table 4. Vector error-correction model results for the GOX grouping

	ΔGOX	ΔGAM	ΔLCAP	ΔMCAP	ΔSCAP
Coint. Eq. 1	-0.0034	0.0307*	-0.0252*	-0.0237	-0.0048
	(-0.1713)	(-3.9375)	(-2.9770)	(-1.7531)	(-0.4870)
ΔGOX(-1)	0.0019	0.0807*	0.0193	0.0282	0.0036
	(-0.0357)	(-3.7843)	(-0.8312)	(-1.1016)	(-0.1313)
ΔGOX(-2)	-0.0104	0.0023	-0.0073	0.0005	-0.0018
	(-0.1922)	(-0.1058)	(-0.3163)	(-0.0210)	(-0.0665)
ΔGAM(-1)	-0.1043	-0.0493	-0.0022	-0.0331	0.0160
	(-0.7915)	(-0.9520)	(-0.0387)	(-0.5326)	(-0.2432)
ΔGAM(-2)	-0.1300	-0.0529	-0.0311	-0.0389	-0.0163
	(-1.0190)	(-1.0543)	(-0.5705)	(-0.6463)	(-0.2569)
ΔLCAP(-1)	-0.4895*	0.0495	-1.1626	-0.061	-0.1012
	(-2.0440)	(-0.9520)	(-0.0387)	(-0.5326)	(-0.2432)
ΔLCAP(-2)	0.2894	0.1187	0.1412	0.2118	0.1926
	(-1.2104)	(-1.2633)	(-1.3835)	(-1.8784)	(-1.6160)
ΔMCAP(-1)	0.3311	-0.0549	0.3199*	0.1545	0.3400
	(-0.8987)	(-0.3792)	(-2.0346)	(-0.8889)	(-1.8517)
ΔMCAP(-2)	-0.4115	-0.0831	-0.1284	-0.3344	-0.2896
	(-1.1232)	(-0.5773)	(-0.8212)	(-1.9353)	(-1.5855)
ΔSCAP(-1)	0.2537	-0.0010	-0.2603*	-0.1487	-0.2480
	(-0.9583)	(-0.0100)	(-2.3046)	(-1.1910)	(-1.8791)
ΔSCAP(-2)	0.2317	-0.0337	0.0000	0.1540	0.1055
	(-0.8835)	(-0.3268)	(-0.0003)	(-1.2451)	(-0.8072)

*Indicates significant at the 5 percent level. t-statistics are in parentheses, below the coefficients. GOX: CBOE Gold Index; GAM: Gold price, morning fixing at London LCAP: S&P 500 Index; MCAP: S&P Midcap 400 Index; SCAP: S&P Smallcap 600 Index.

What is an appropriate interpretation of the Granger causality results? A decline in the broad stock market may prompt investors to become interested in investing in gold. However, there are several ways this can be done. In addition to investing in gold itself there is the possibility of investing in gold mining company stocks. Some investors may face restrictions that could limit their ability to invest directly in the commodity; increasing holdings in gold mining company stocks could offer an alternative way to increase a position with respect to gold. An increase in gold mining company stock prices may provide information, a signal to investors, to increase positions in gold itself.

Variance decompositions and impulse response functions clarify how each series in the GOX grouping responds to shocks by the other series and thus helps provide additional insight into the interdependence between the indexes. Impulse responses measure the dynamic effect on each series from a one-standard deviation shock to each series. There is a lesser degree of interdependence (or a greater degree of independence) between the series if responses to shocks are small and are not persistent over time. Figure 2 presents graphs of the impulse response functions for the GOX grouping. For example, the graphs on the first row represent the responses by the gold mining company stock price index, GOX, to shocks from each index series while the graphs on the first column represents the responses of each index to shocks from GOX. Similarly, the graphs on the second row correspond to the responses by the gold stock price index, GAM, to a shock from each index series while the graphs on the second column correspond to the responses of each index series to a shock from GAM, and so on. For each graph, the vertical axis indicates the approximate percentage point change in the index due to a one-standard deviation shock in a given endogenous series in the GOX grouping and the horizontal axis shows the responses up to 52 weeks.

The overall pattern for the GOX grouping is one of persistence rather than temporary disturbance and indicates a relatively high degree of interdependence among the index series in the grouping. Interestingly, the GOX response to shocks to gold prices and large capitalization stock prices is relatively small. However, a shock to GOX does have a larger, positive, and persistent impact on gold prices. The LCAP index responds negatively and persistently to shocks to GOX and positively and persistently to GAM; the latter effect is puzzling.

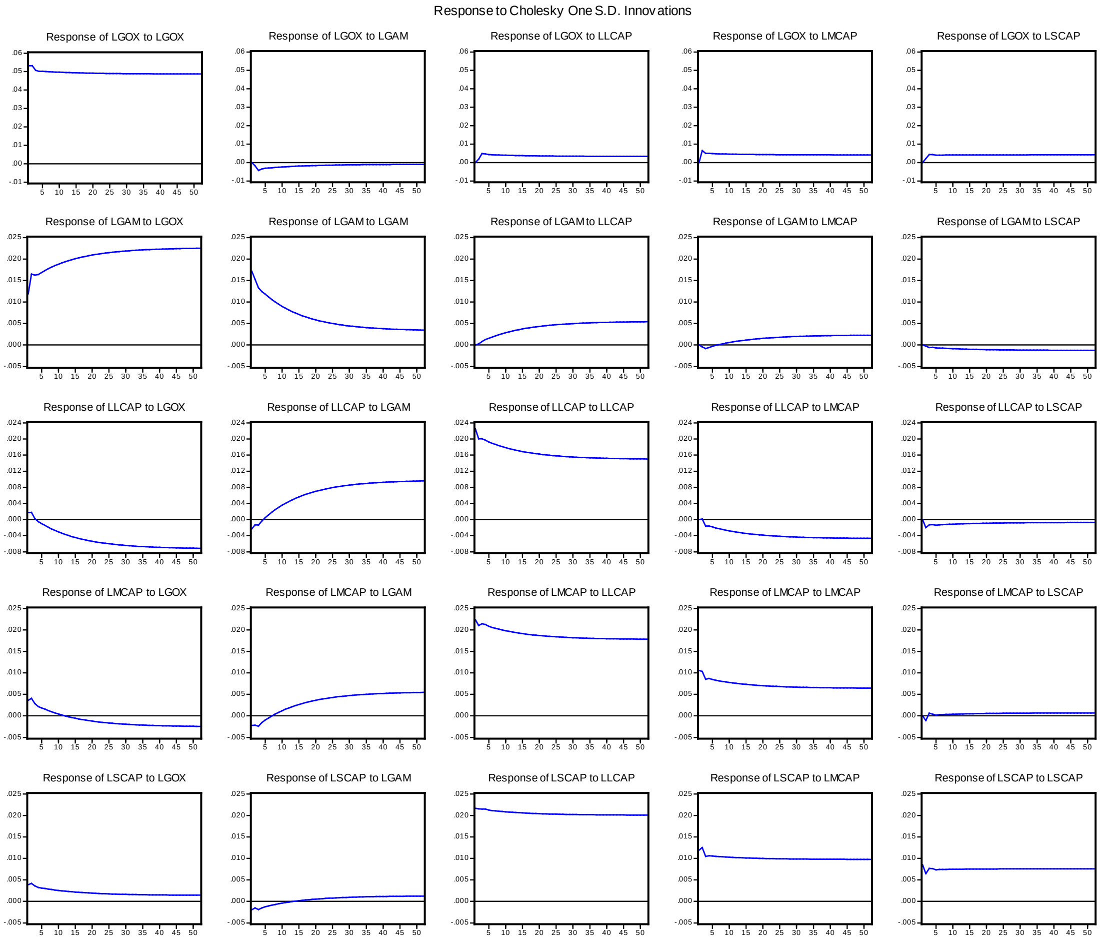

Figure 2. Impulse Responses for the GOX Grouping

Variance decompositions of the forecast errors are also used to further examine the nature of the short-term relationships in the GOX grouping. Variance decompositions measure the proportion of the forecast error variance of each series that is explained by its own innovation and by innovations from the other series in the grouping. There is a lesser degree of interdependence (or a greater degree of independence) when a series is shocked and a greater (lesser) proportion of its forecast error variance can be attributed to its own innovation rather than innovations from the other series. Table 5 reports the percentages of the forecast error variance in each index series that can be explained by its own innovation (on the diagonal) and by innovations from other series (off the diagonal) at horizons of 1 week, 26 weeks, and 52 weeks.(Note 6) The gold mining company stock price index, GOX, and the large capitalization stock price index, LCAP, exhibit the greatest relative independence with 100%/97.84%/97.94% and 98.38%/84.07%/72.51% of their own forecast error variance explained, respectively, at the three horizons. Next is the gold price index, GAM (67.36%/17.85%/9.80%), followed by the midcap and the smallcap stock indices. In some cases, one or more index series explain more of the forecast error variances than the index series being shocked. More specifically, GOX explains an increasing proportion at longer horizons (32.64%/79.20%/85.54%) of the forecast error variance of the gold price index, GAM. These results point to a lesser degree of independence for GAM as opposed to the

GOX and LCAP. Overall, the variance decomposition again indicates a degree of relative interdependence within the GOX grouping.

Table 5. Variance decomposition results for the GOX grouping

Horizon	Proportion of forecast error variance explained by shocks to				
	GOX	GAM	LCAP	MCAP	SCAP
Series explained – GOX					
1	100.00	0.00	0.00	0.00	0.00
26	97.84	0.19	0.55	0.80	0.62
52	97.94	0.13	0.51	0.76	0.67
Series explained – GAM					
1	32.64	67.36	0.00	0.00	0.00
26	79.20	17.85	2.49	0.28	0.18
52	85.54	9.80	3.84	0.58	0.23
Series explained – LCAP					
1	0.57	1.05	98.38	0.00	0.00
26	4.65	7.98	84.07	2.78	0.32
52	8.44	14.78	72.51	4.05	0.24
Series explained – MCAP					
1	2.06	0.80	79.44	17.7	0.00
26	0.60	1.68	84.38	13.28	0.06
52	0.90	14.78	82.93	12.13	0.08
Series explained – SCAP					
1	2.13	0.53	66.82	20.24	10.29
26	1.08	0.13	71.63	17.78	9.38
52	0.76	0.17	71.83	17.46	9.77

In percentage terms,, the rows may not sum to 100 due to rounding error. GOX: CBOE Gold Index; GAM: Gold price, morning fixing at London LCAP: S&P 500 Index; MCAP: S&P Midcap 400 Index; SCAP: S&P Smallcap 600 Index.

3.4 Tests for the Dynamics of the HUI Grouping

Although the results of the multilateral cointegration tests indicate that there is no long-run relationship involving the gold mining stock price index HUI, the gold price index (GAM or GPM), and the three stock market price indices (LCAP, MCAP and SCAP), the possibility of short-run relationships remains. Since the five index series are not cointegrated, a Vector Autocorrelation (VAR) model in log first differences is constructed, with three lags to avoid residual-term autocorrelation. The VAR model results are presented in Table 6. Similarly to the results using the GOX index, short-term Granger causation is found to run from the HUI index to the gold price index (with a positive sign), but there is no reverse causality. The coefficients for the lagged large capitalization stock price index, LCAP, are not statistically significant but do have the negative sign as was the case with the GOX grouping. Thus, this

VAR representation yields essentially the same relationships between LCAP and HUI, and between HUI and GAM.

Table 6: Vector autocorrelation model results for the HUI grouping

	ΔHUI	ΔGAM	ΔLCAP	ΔMCAP	ΔSCAP
ΔHUI(-1)	0.0110	0.0957*	-0.0130	0.0041	-0.0143
	(-0.2062)	(-4.4763)	(-0.5662)	(-0.1635)	(-0.5392)
ΔHUI(-2)	0.0021	0.0019	-0.0240	-0.0075	0.0007
	(-0.0374)	(-0.0850)	(-1.0154)	(-0.2876)	(-0.0027)
ΔHUI(-3)	-0.0157	0.0120	-0.0305	0.0001	0.0146
	(-0.2902)	(-0.5579)	(-1.3116)	(-0.0024)	(-0.5434)
ΔGAM(-1)	-0.0894	-0.0958	0.0348	-0.0082	0.0365
	(-0.6737)	(-1.1305)	(-0.6094)	(-0.1309)	(-0.5532)
ΔGAM(-2)	-0.1745	-0.0554	-0.0109	-0.0423	-0.036
	(-1.3042)	(-1.0390)	(-0.1899)	(-0.6691)	(-0.5400)
ΔGAM(-3)	0.0353	-0.0242	0.0403	-0.0077	-0.008
	(-0.2711)	(-0.4670)	(-0.7194)	(-0.1260)	(-0.1233)
ΔLCAP(-1)	-0.3273	0.0164	-0.1070	-0.0110	-0.0599
	(-1.3614)	(-0.1712)	(-1.0348)	(-0.0970)	(-0.5002)
ΔLCAP(-2)	0.1998	0.0585	0.2014	0.2628*	0.2364*
	(-0.8305)	(-0.6101)	(-1.9459)	(-2.3129)	(-1.9746)
ΔLCAP(-3)	-0.0739	-0.1674	-0.0372	-0.0105	0.0266
	(-0.3117)	(-1.7708)	(-0.3646)	(-0.0939)	(-0.2257)
ΔMCAP(-1)	0.1118	-0.0286	0.2564	0.0885	0.2752
	(-0.3737)	(-0.1491)	(-0.1608)	(-0.1765)	(-0.1860)
ΔMCAP(-2)	-0.3499	-0.0228	-0.1665	-0.3729*	-0.3234
	(-0.9268)	(-0.1513)	(-1.0247)	(-2.0910)	(-1.7210)
ΔMCAP(-3)	0.4202	0.1363	-0.0683	-0.0102	-0.0400
	(-1.1348)	(-0.9226)	(-0.4285)	(-0.0583)	(-0.0217)
ΔSCAP(-1)	0.2843	-0.0117	-0.2504*	-0.1346	-0.2226
	(-1.0643)	(-0.1097)	(-2.1791)	(-1.0670)	(-1.6744)
ΔSCAP(-2)	0.2199	-0.0275	-0.0143	0.1443	0.1006
	(-0.8150)	(-0.2552)	(-0.1235)	(-1.1325)	(-0.7494)
ΔSCAP(-3)	-0.0682	0.0633	0.1398	0.0758	0.0987
	(-0.2568)	(-0.5983)	(-1.2240)	(-0.6042)	(-0.7471)

*Indicates significant at the 5 percent level. t-statistics are in parentheses, below the coefficients. HUI: AMEX Gold Index; GAM: Gold price, morning fixing at London. LCAP: S&P 500 Index; MCAP: S&P Midcap 400 Index; SCAP: S&P Smallcap 600 Index.

In contrast to the results for the GOX grouping, the graphs of the impulse response functions involving the HUI grouping presented in Figure 3 show only short-term (ten weeks or less), very limited effects. This indicates a relatively higher degree of independence between the index series in the HUI grouping. The strongest responses are the positive reaction of the gold price (GAM) series a shock to the gold mining company stock price HUI index, as well as the responses by the MCAP and SCAP to a shock to LCAP.

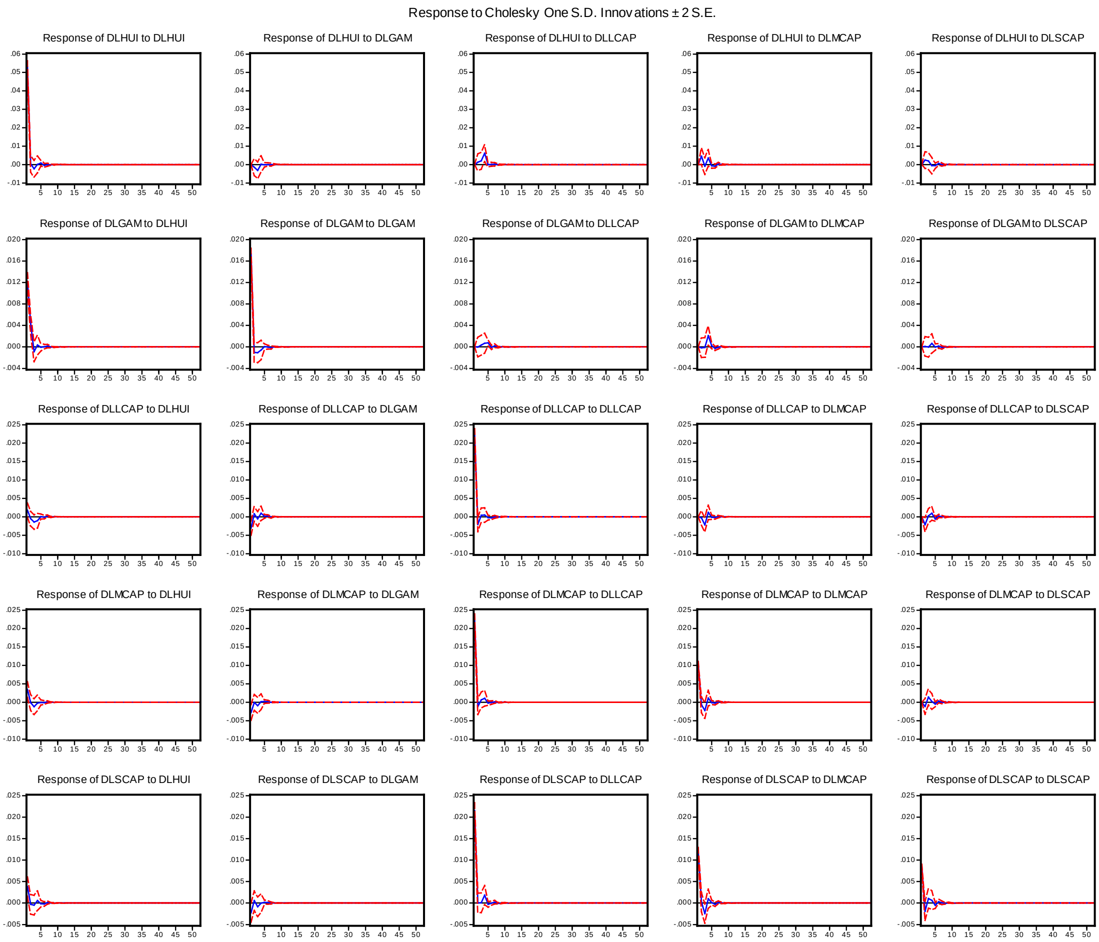

Figure 3. Impulse Responses for the HUI Grouping

Contrary to the GOX grouping, the variance decomposition results for the HUI grouping, shown in Table 7, reveal that the proportions of the forecast error variance are already stable by 26 weeks. There is nevertheless similarity with the GOX grouping results: the HUI and the LCAP indexes show the greatest relative independence with 100%/96.48%/96.48% and 97.57%/94.44%/94.44% of their own forecast variance explained, respectively, followed by the GAM index (66.98%/63.55%/63.55%), the MCAP index (17.40%/18.04%/18.04%) and the SCAP index (10.40%/10.91%/10.91%). The GAM index, however, explains a greater proportion of its own forecast error variance in the HUI grouping (66.98%/63.55%/63.55%) than in the GOX grouping (67.36%/17.85%/9.80%) as the GOX index explains an increasing proportion of the forecast error variance of the gold price index (32.64%/79.20%/85.54%) while the HUI index does not (33.02%/35.12%/35.12%).

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4. Conclusion

This paper investigates the dynamic relationships between two gold price series (morning and afternoon fixing in London), two gold mining company stock price indexes (GOX and HUI) and three stock market indices representing large, mid and small capitalization stocks over the 1996-2007 period. Multivariate cointegration tests are performed to investigate long-term comovements between the series, while allowing for the possibility of short-run divergences. Variance decompositions and impulse response functions are also employed to describe the long- and short-run dynamics of the series.

Table 7. Variance decomposition results for the HUI grouping

Horizon	Proportion of forecast error variance explained by shocks to				
	HUI	GAM	LCAP	MCAP	SCAP
Series explained – HUI					
1	100.00	0.00	0.00	0.00	0.00
26	96.48	0.43	1.50	1.22	0.37
52	96.48	0.43	1.50	1.22	0.37
Series explained – GAM					
1	33.02	66.98	0.00	0.00	0.00
26	35.12	63.55	0.25	0.97	0.10
52	35.12	63.55	0.25	0.97	0.10
Series explained – LCAP					
1	0.62	1.81	97.57	0.00	0.00
26	1.24	2.08	94.44	1.15	1.10
52	1.24	2.08	94.44	1.15	1.10
Series explained – MCAP					
1	1.94	1.23	79.43	17.40	0.00
26	2.13	1.34	77.92	18.04	0.58
52	2.13	1.34	77.92	18.04	0.58
Series explained – SCAP					
1	2.09	0.73	66.44	20.34	10.40
26	2.14	0.87	65.24	20.84	10.91
52	2.14	0.87	65.24	20.84	10.91

In percentage terms, the rows may not sum to 100 due to rounding error. HUI: AMEX Gold Index; GAM: Gold price, morning fixing at London LCAP: S&P 500 Index; MCAP: S&P Midcap 400 Index; SCAP: S&P Smallcap 600 Index.

One cointegrating relationship between the series in the GOX grouping is found, indicating long-run interdependence between them (and reduced benefits from diversification); this was the case whether the morning or the afternoon gold price fixing was used. A vector error-correction (VEC) model reveals that both gold and large capitalization stock prices tend to restore the long-term equilibrium following shocks to the variables, with the gold price series adjusting more rapidly. There are short-term causal relationships running from the large capitalization stock price index (LCAP) to the gold mining company stock price index (GOX) and from the GOX to gold prices (GAM or GPM), but not the reverse. Variance decompositions and impulse responses indicate a fairly high degree of interdependence among the series in the GOX grouping. In contrast, the HUI grouping is not cointegrated, regardless of which gold price series is used. A vector autoregression (VAR) model in first differences yields essentially the same relationships between the large capitalization stock price index, the HUI, and gold prices. Impulse response functions and variance decompositions reveal a lower degree of interdependence among those variables than in the GOX grouping.

Notes

Note 1. We also performed our methodology using daily data and obtained essentially the same results.

Note 2. In an equal-dollar weighted index, each component stock is represented in approximate equal dollar market value, say $10,000. The index is calculated by establishing an aggregate market value for every component stock and then determining the number of shares of each stock by dividing this aggregate market value by the current price of the stock. Additionally, the weights of each component stock are reset to equal values at regular intervals (e.g. quarterly). Many of the relatively small size sector indices use the equal-dollar method so that each stock exerts an equal influence on the performance of the overall index.

Note 3. A modified equal-dollar weighted index does not necessarily reset component stocks to equal values.

Note 4. The results are qualitatively the same whether we use opening (GAM) or closing (GPM) gold price series. Similar results are also obtained on cointegration tests using daily and monthly data and are, therefore, not reported here.

Note 5. Although the Schwartz Criteria indicate one lag for the VEC model, two lags are needed to assure that the residuals are free from autocorrelation.

Note 6. Since the results depend on the ordering of the series, different orderings were compared; the qualitative results were similar, particularly at the longer horizons.

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Appendix 1. Cointegration Analysis

This appendix presents some of the mathematical details of cointegration theory. If there are two variables, xt and yt, which are both nonstationary in levels but stationary in first differences, then xt and yt are integrated of order one, I(1), and their linear combination having the form

$$z_t = x_t - ay_t \qquad (1)$$

is generally also I(1). However, if there is an (a) such that z_t is integrated of order zero, I(0), the linear combination of x_t and y_t is stationary and the two variables are said to be cointegrated (Engle and Granger, 1987). If two variables are cointegrated, there is an underlying long-run relationship between them. In the short run the series may drift apart, but if they are cointegrated, they will move toward long-run equilibrium through the error-correction mechanism.

The first step in the analysis is to test each series for the presence of unit roots. This can be done by means of the Augmented Dickey Fuller (ADF) test, an extension of the Dickey and Fuller (1981) method. The ADF test uses a regression of the first differences of the series against the series lagged once, and lagged difference terms, with optional constant and time trend terms:

$$\Delta y_t = a_0 + a_1 t + \gamma y_{t-1} + \Sigma b_i y_{t-i+1} + e_t \qquad (2)$$

In the equation Δ is the first difference operator, a_0 is an intercept, $a_1 t$ is a linear time trend, e_t is an error term, and i is the number of lagged first-differenced terms such that e_t is white noise. The test for a unit root has the null hypothesis that $\gamma = 0$. If the coefficient is significantly different from zero, the hypothesis that y_t contains a unit root is rejected. If the test on the level series fails to reject, the ADF procedure is then applied to the first-differences of the series. Rejection leads to the conclusion that the series is integrated of order one, I(1).

A limitation of the Dickey-Fuller test is that it assumes that the errors are statistically independent and have a constant variance. In 1988, Phillips and Perron (PP) generalized the ADF test:

$$y_t = b_0 + b_1 y_{t-1} + b_2(t - T/2) + \mu_t \qquad (3)$$

T is the number of observations and the disturbance term μ_t is such that $E(\mu_t) = 0$, but there is no requirement that the disturbance term is serially uncorrelated or homogeneous. The equation is estimated by ordinary least squares and the t-statistic of the b_1 coefficient is corrected for serial correlation in μ_t using the Newey-West (1987) procedure for adjusting the standard errors.

The Johansen (1988) approach to testing for cointegration relies on the relationship between the rank of a matrix and its characteristic roots, or eigenvalues. Let X_t be a vector of n time series variables, each of which is integrated of order (1), and assume that X_t can be modeled by a vector autoregression (VAR):

$$X_t = A_1 X_{t-1} + \ldots + A_p X_{t-p} + \varepsilon_t \qquad (4)$$

Rewrite the VAR as

$$\Delta x_t = \Pi x_{t-1} + \Sigma \Gamma \Delta x_{t-i} + \varepsilon_t \qquad (5)$$

where $\Pi = \Sigma A_i - I$, $\Gamma_i = - \Sigma A_i$. If the coefficient matrix Π has reduced rank $r < k$, there exist k x r matrices α and β each with rank r such that $\Pi = \alpha\beta'$ and $\beta' x_t$ is stationary. The number of cointegrating relations is given by r, and each column of β is a cointegrating vector. Three cases are possible. First, if Π is of full rank, all elements of X are stationary, and none of the series has a unit root. Second, if the rank of $\Pi = 0$, there are no combinations which are stationary and there are no cointegrating vectors. Third, if the rank of Π is r such that $0 < r < k$, then the X variables are cointegrated and there exist r cointegrating vectors. Equation (8) can be modified to allow for an intercept and a linear trend.

The number of distinct cointegrating vectors can be obtained by determining the significance of the characteristic roots of Π. To identify the number of characteristic roots that are not different from unity we use two statistics, the trace test and the maximum eigenvalue test:

$$\lambda_{trace}(r) = -T\Sigma\ln(1 - \lambda_i) \qquad (6)$$

and

$$\lambda_{max}(r,r+1) = -T\ln(1 - \lambda_{r+1}) \qquad (7)$$

where λ_i = the estimated values of the characteristic roots (eigenvalues) obtained from the estimated Π matrix, r is the number of cointegrating vectors, and T = the number of usable observations. The trace test evaluates the null hypothesis that the number of distinct cointegrating vectors is less than or equal to r against a general alternative. The maximum eigenvalue test examines the number of cointegrating vectors versus that number plus one. If the variables in X_t are not cointegrated, the rank of Π is zero and all the characteristic roots are zero. Since ln(1) = 0, each of the expressions $\ln(1 - \lambda_i)$ will equal zero in that case. Critical values for the test are provided by Johansen and Juselius (1990) and by Osterwald-Lenum (1992).