Zheng-Wei Lin (Taiwan), Chia-Cheng Chen (Taiwan), Chin-Sheng Huang (Taiwan)

Profits from technical analysis: an empirical evidence of precious metal markets

Abstract

The main objective of this study is to investigate the validity and predictability of technical analysis in precious metal markets. This study applies the bootstrap tests of White (2000) and Hansen (2005) to determine if there are favorable trade rules among the "universe" of technical trading rules of the Sullivan et al. [3] research. This study employs the powerful bootstrap tests to determine the profitability of technical analysis with the restructuring of non-synchronous trading and transaction costs. The empirical results strongly indicate that the three elements, data snooping, non-synchronous trading and transaction costs, have a significant impact on the overall performance of technical analysis. In fact, these results illustrate that economic profits cannot be generated among the ten precious metal market indices.

Keywords: technical analysis, data snooping, bootstrap tests.
JEL Classification: G15, F37.

Introduction

Technical analysis is a well-established method of forecasting future market movements by generating buy or sell signals based on specific information gained from previous prices. The continuing prevalence and application of technical analysis has come to be widely recognized, even among academic scholars, with the techniques for discovering any hidden patterns ranging from the very rudimentary analysis of moving averages, to the recognition of quite complex time series patterns. Brock et al. (1992) show that simple trading rules based upon the movements of a short-run and a long-run moving average return have significant predictive power over a century of daily data on the Dow Jones industrial average. Fifield, Power, and Sinclair (1995) went on to investigate the predictive power of the "filter" rule and the "moving average oscillator" rule in eleven European stock markets covering the period from January 1991 to December 2000. Their main findings indicated that four emerging markets, Greece, Hungary, Portugal and Turkey, were informationally inefficient, relative to the other seven more advanced markets. Empirical results in the past support technical analysis among them (Blume et al., 1994; Lo et al., 2000; and Savin et al., 2007). However, such evidences may be criticized for their data snooping bias. (e.g., Lo and MacKinlay, 1990; and Brock et al., 1992).

Data snooping occurs when a given set of data is used more than once for purposes of inference or model selection. When such data reuse occurs, there is always the possibility that any satisfactory results obtained may simply be due to chance rather than to any merit inherent in the method yielding the results. This problem is practically unavoidable in the analysis of time-series data, as typically only a single history measuring a given phenomenon of interest is available for analysis. It is widely acknowledged by empirical researchers that data snooping is a dangerous practice to be avoided but in fact it is endemic. The main problem has been a lack of sufficiently simple practical methods capable of assessing the potential dangers of data snooping in a given situation. Sullivan et al. (1999) apply the White (2000) "reality check (RC)" test and find that technical trading rules lose their predictive power for major U.S. stock indices after the mid 80s. Chen et al. (2009) find that the results of technical analysis remain valid in all Asian markets, with the exception of South Korea, even after controlling for data snooping bias through the bootstrap reality check (RC) of White (2000) and superior predictive ability (SPA) test of Hansen (2005). Hsu et al. (2010) extend the SPA test of Hansen (2005) to a stepwise SPA test that can identify predictive models without potential data snooping bias. In the present study, we set out to empirically test the efficacy of technical analysis within thirteen precious metal market indices, employing the two data snooping adjustment methods for non-synchronous trading and transaction costs proposed by White (2000) and Hansen (2005).

The efficient market hypothesis (EMH) has dominated empirical finance, largely as a result of the work of Fama (1970). An enormous wealth of associated literature during the 1970s provided support for the weak form of this hypothesis, in which it is suggested that changes in past share prices cannot be used to forecast future share returns. Along the same vein, precious metal market efficiency implies that precious metal prices respond quickly and accurately to relevant information. If precious metal prices are mean reverting, then it follows that the price level will return to its trend path over time and that it might be possible to forecast future movements in precious metal prices based on past behavior. By contrast, if precious metal prices follow a random walk process, then any shock to prices is permanent. This means that future returns cannot be predicted based on historical movements in precious metal prices and that volatility in precious metal markets increases without bound.

Historically, technical analysis is equally appealed among financial and agricultural commodity markets as illustrated by popular practitioner books, for examples, Murphy (1986), Arnold (1993), and Pring (2002). The most widely followed futures composite index is the commodity research bureau (CRB) index represents basket of 21 industrial and agriculture commodities. The CRB index is particularly sensitive to price movement in the grains and oil complex. However, as surveyed by Park and Irwin (2007), most empirical studies of the efficacy of technical analysis concentrate on stock markets and foreign exchange markets. Only a smaller number of studies devote to commodity markets, in particular, precious metal markets.

MacDonald and Taylor (1988a) used the bivariate vector autoregressive approach with appropriate stationarity-inducing transformations to test the efficient market hypothesis in terms of four primary metals quoted on the London metal exchange. The metals studied are copper, lead, tin and zinc over the period from January 1976 to March 1987. They demonstrated the rejection of the joint efficient markets hypothesis for copper and lead of the four examined metals. Besides, MacDonald and Taylor (1988b) focused on the market efficiency of metals prices from the London metal exchange. Their main finding concerns the result that none of their chosen spot metal prices are cointegrated and supports the efficient markets hypothesis.

Sephton and Cochrane (1990) examined the market efficiency hypothesis with respect to six metals traded on the London metal exchange (LME). Using overlapping data and both single and multimarket models, they found evidence contradictory to the tenet that the LME is an efficient market.

Jones and Uri (1990) investigated the efficiency of three primary metals markets in the USA using both static cointegration and dynamic error correction tests. The spot prices of lead, tin and zinc over the period from January 1964 to December 1987 have served as the basis of the analysis. The results showed that spot prices for lead and both, tin and zinc, are cointegrated at the 1% level. This fact meant that these markets are not efficient in the semistrong form sense since casuality must run in at least one direction.

Sephton and Cochrane (1991) suggested that some markets on the LME do not exhibit the major characteristics of efficient markets: rationality and risk neutrality. They pointed that the tin market exhibited a risk premium and was inefficient between 1976 and 1985. Narayan et al. (2010) examined the long-run relationship between gold and oil spot and futures markets. They tested for the long-run relationship between gold and oil futures prices at different maturity and unravel evidence of cointegration. The evidence of Narayan et al. (2000) indicated that the oil market can be used to predict the gold market prices and vice versa, thus, these two markets are jointly inefficient.

We set out in this study to test empirically the profitability of technical analysis in ten precious metal market indexes of futures and spots over the period from January 1968 to December 2009, taking into account the relevant data snooping biases, nonsynchronous trading effects and transaction costs. We reexamine the performance of technical rules by implementing the White (2000) "reality check" and the Hansen (2005) "superior predictive ability" test in order to fully investigate the effects that data snooping can have on trading rules. Our study extends the set of trading rules considered in Bessembinder and Chan (1995) to the "universe" of 7846 trading spaces suggested in Sullivan, Timmermann, and White (1999).

The remainder of this paper is organized as follows. An explanation of the test algorithms and the trading rules proposed in this study is provided in Section 1. Section 2 presents our presentation and subsequent analysis of the empirical results. Finally, the conclusions drawn from this study are provided in the last Section, along with some suggestions for further development of our approach.

1. Methodology

In this Section, we describe the methodology used in our study, including the test algorithms and the trading rules. The former comprises the "reality check" of White (2000) and the "superior predictive ability" test of Hansen (2005), while the latter introduces the 7846 universal rules proposed by Sullivan et al. (1999).

1.1. The reality check and superior predictive ability tests. Trading model dependence makes it difficult to construct a formal test to differentiate between a genuine model with superior predictability and other spurious models. White's "reality check", which initially built on Diebold and Mariano (1995) and West (1996), employed the block resampling procedure of Politis and Romano (1994) in a predictive power test model to account for the effect of data mining.

We begin by defining the relative performance of models k, k =1, ..., m, against the benchmark at time t, t =1, ..., n, as follows:

$$\pi_{k,t} \equiv \phi(\xi_t, \delta_{k,t-1}) - \phi(\xi_t, \delta_{0,t-1}), \quad k = 0,1,\ldots,m \quad (1)$$

$$\phi(\xi_t, \delta_{k,t-1}) = \delta_{k,t-1}\ \xi_t,$$

where ξ_t represents the random real asset returns; $\delta_{k,t-1}$ is the trading signal of the forecasting model k, at $t-1$; and $k = 0$ represents the market model.

Let $\mu_k = E(\pi k)$ be the expected excess return of model k. As we are interested to know whether any of the models are better than the benchmark, the natural null hypothesis of interest can then be defined as:

$$H_0 : \max_{k=1,\ldots,m} \mu_k \leq 0. \quad (2)$$

Rejection of this null hypothesis leads to the existence of the best technical trading rule achieving performance superior to the benchmark. The block re-sampling procedure of Politis and Romano (1994) is employed to generate 500 pseudo time-series $\pi^B_{k,\ t}$ from the observed value $\pi_{k,\ t}$. We construct the following two statistics from both, the real series and the pseudo series:

$$T_n^{RC} = \max_{1<k<m}(n^{1/2}\overline{\pi}_k) \quad T_n^{RC.B} = \max_{1<k<m}(n^{1/2}(\overline{\pi}_k^B - \overline{\pi}_k)). \quad (3)$$

The comparison between T_n^{RC} and the $T_n^{RC.B}$ quintiles provides the White (2000) p-value for the null hypothesis test. The "superior predictive ability" test of Hansen (2005), the development of which was based upon White's "reality check", provides an alternative method of correcting the findings for data snooping effects. Hansen (2005) demonstrated that the "reality check" can be seriously manipulated by other irrelevant models, resulting in reduced test power, and therefore utilized the studentized process to remove the irrelevant models in the sample. Similar to White (2000), the two statistics are provided as:

$$T_n^{SPA} = \max[\max_{k=1\ldots m} \frac{n^{1/2}\overline{\pi}k}{\hat{\omega}k}, 0] \quad T_n^{SPA,B} = \max[\max_{k=1\ldots m} \frac{n^{1/2}(\overline{\pi}_k^B - \hat{\mu}_k^c)}{\hat{\omega}k}, 0], \quad (4)$$

where $\hat{\omega}k$ is a consistent estimator for return variance, calculated by the stationary bootstrap method of Politis and Romano (1994), and $\hat{\mu}_k^c = \overline{\pi}_k 1_{\{n^{1/2}\ \overline{\pi}_k\ /\ \hat{\omega}k \leq -2\sqrt{log\ log\ n}\}}$ is the threshold used for the removal of the irrelevant models. The comparison between T_n^{SPA} and $T_n^{SPA,B}$ quartiles provides the p-value for the Hansen (2005) "superior predictive ability" null hypothesis test.

1.2. Technical analysis. Sullivan et al. (1999) extended the sample rules proposed by Brock et al. (1992), to a larger universal technical analysis space. In this paper, we adopt the two sets of rule spaces proposed in these two studies, and undertake a comprehensive comparison of their performance. The Sullivan et al. (1999) trading set comprises of 7846 universal trading rules belonging to five technical analysis catalogs, as shown in the following sub-sections, each of which provides a brief overview of these rules.

1.2.1. Filter rules. The standard filter rule can be explained as in Fama and Blume (1966, p. 227).

We define an X per cent filter as follows. If the daily closing price of a particular security moves up by at least X percent, then an investor buys and holds the security until its price moves down at least X per cent from the subsequent high, at which time the investor simultaneously sells and takes up a short position. This short position is maintained until the daily closing price rises by at least X per cent above the subsequent low, at which time the investor covers and buys. Any movements of less than X percent in either direction are ignored.

In executing the filter rule, this study relies upon four parameters: (1) a change in the share price required to initiate a position (ranging from 0.005 to 0.5, giving a total of 24 values); (2) a change in the share price required to liquidate a position (ranging from 0.005 to 0.2, giving a total of 12 values); (3) an alternative definition of extremes, where a low (high) can be defined as the most recent closing price which is less (greater) than the n previous closing prices (ranging from1 to 20, giving a total of eight values); and (4) the number of days a position is held (5, 10, 25 or 50 days, giving a total of four values). The various permutations of the above four parameters result in the construction of a total of 497 filter rules.

1.2.2. Moving average (MA) rules. A moving average strategy is designed to detect a trend with a buy (sell) signal, being generated when the short-term average price crosses the long-term average price from below (above). The execution of a moving average rule relies on five parameters: (1) the number of days for the short-run moving average (ranging from 2 to 250, giving a total of 15 values); (2) the number for the long-run moving average, and combination of the short-run and long-run moving average give a total number of 105; (3) a fixed band multiplicative before a signal is recognized to avoid small difference between the short-run and long-run moving average (ranging from0.001 to 0.05, giving a total of eight values); (4) the number of days in the time delay before the signal is acted upon (2, 3, 4 or 5 days, giving a total of four values); and (5) the number of days that a position is held (5, 10, 25 or 50 days, giving a total of four values).

An example of this is MA (1, 2, 0, 0, 0), which represents the moving average as defined by the following five parameters: (1) a 1-day (short-term) average line; (2) a 2-day (long-term) average line; (3) a zero fixed band; (4) no time delay; and (5) a variable holding day. The various permutations of the above five parameters result in the construction of a total of 2049 rules.

1.2.3. Support and resistance rules. A "support and resistance" strategy supplies details on the market movements relating to historical support and resistance lines. A buy (sell) signal is generated when the closing price exceeds (falls below) the historical maximum (minimum) within a given time frame. Similar to the "moving average" rules, the execution of a support and resistance rule relies on five parameters: (1) the number of days in the support and resistance range (ranging from 5 to 250, giving a total of ten values); (2) an alternative definition of extremes, where a low can be defined as the most recent closing price which is less than the previous n closing prices (ranging from 2 to 200, giving a total of ten values); (3) a fixed band multiplicative value (ranging from 0.001 to 0.05, giving a total of eight values); (4) the number of days in the time delay (2, 3, 4 or 5 days, giving a total of four values); and (5) the number of days that a position is held (5, 10, 25 or 50 days, giving a total of four values). The various permutations of the above five parameters result in the construction of a total of 1220 rules.

1.2.4. Channel breakout rules. A "channel breakout" strategy is similar to the support and resistance rule. The buy (sell) signal is generated when the closing price moves up (down) the upper (lower) channel. The execution of a channel breakout rule is reliant upon the following four parameters: (1) the number of days in the channel (ranging from 5 to 250, giving a total of ten values); (2) the difference between the high and low price required to form a channel (ranging from 0.005 to 0.15, giving a total of eight values); (3) a fixed band multiplicative value (ranging from 0.001 to 0.05, giving a total of eight values); and (4) the number of days that a position is held (5, 10, 25 or 50 days, giving a total of four values). The various permutations of the above five parameters result in the construction of a total of 2040 rules.

1.2.5. On-balance volume average (OBV) rule. An "on-balance volume averages" strategy is a volume-based version of the moving average rules. A buy (sell) signal is generated when the short-term average volume crosses the on-term average volume from below (above). The parameters required in the on-balance volume averages strategy are similar to those for the moving average rules. This category has a total of 2040 rules.

1.3. Implementation. First, we apply the 7846 trading rules of universe of Sullivan et al. (1999) to the time series of ten precious metal price indices. For example, a certain type of moving average trading indicator, MA (1, 250, 0, 0, 10), generates a trading signal of buying, selling, or neutral on each trading day for the gold bullion spot index (LBM) as follows. When the current price crosses the long-term moving average of 250-day prices from below (above) then a buy (sell) signal is generated with long position (short position) of +1 (-1). The trading signal effects on the immediate trading day and holds for the following 10 days. The performance statistic of the MA (1, 250, 0, 0, 10) for LBM is set as:

$$\bar{f} = n^{-1} \sum_{t+R}^{T} \hat{f}_{t+1}, \quad (5)$$

where n is the number of prediction periods of LBM indexed from R through T so that $T = R + n - 1$, $\hat{f}_{t+1}$ is the realized performance measure for the day $t + 1$. Specifically, in the sample of LBM, n is set equal to 10697, R is set equal to 251, accommodating the technical indicators that require 250 previous daily data in order to produce trading signals. The performance measure is exactly defined as follows:

$$f_{k,t+1} = \ln[1 + y_{t+1} S_k(\chi_t, \beta_k)] - \ln[1 + y_{t+1} S_k(\chi_t, \beta_0)], \quad (6)$$

where $\chi_t = \{X_{t-i}\}_{i=0}^{R}$, X_t is the original price series of LBM, $y_{t+1} = (X_{t+1} - X_t)/X_t$, and $S_k(.)$ and $S_0(.)$ are respectively signal functions of trading rule k (here, MA (1, 250, 0, 0, 10)) and the buy-and-hold strategy that convert the sequence of price index information χ_t into trading signals of long position of +1, short position of -1, and neutral position of 0. The $f_{k,t+1}$ represents the relative trading return of the trading rule k with respective to the buy-and-hold strategy on the day $t + 1$.

Second, repeat the first step for all k = 1,.., 7846 rules on the price series of LBM and complete the computation of relative performance measures of the full universe of Sullivan et al. (1999). This study then examines the profitability of technical analysis on LBM in terms of nominal data snooping test, non-synchronous trading adjustment, transaction costs adjustment, and White's (2000) and Hansen's (2005) bootstrapping tests. The nominal data snooping test of this study is inherently the performance test of Brock et al. (1992). This study also follows the one-day lag adjustment proposed by Bessembinder and Chan (1995) to partially calibrate the non-synchronous bias. Specifically, we associate the day $t + 2$ return with the initial trading signal emitted at the close of day t, thereby allowing the component stocks of the index to be fully traded on the intervening days. We incorporate the transaction costs of the ten precious metal market indices into the analysis of the profitability of technical analysis in this study. The round-trip costs utilized in this study are drawn from the member fees of CME group and range from the highest high grade copper futures index (CMX) of 0.5% to the lowest copper, grade a cash spot index (LME) of 0.02%. Finally, this study adjusts the performance of technical analysis for data snooping bias by employing the White (2000) "reality check" and the Hansen (2005) "superior predictive ability" test as illustrated in the Section 1.1.

2. Empirical results and analysis

We set out in this study to test empirically the profitability of technical analysis of Sullivan et al. (1999) in precious metal market indices over the period of 1968-2009, taking into account the relevant data snooping biases, non-synchronous trading effects and transaction costs. The testing markets indices cover ten precious metal markets which are comprised of five futures: high grade copper futures index (CMX), gold 100 OZ futures index (CMX), palladium futures index (NYM), platinum futures index (NYM), silver 5000 OZ futures index (CMX), as well as five spots: copper, grade a cash spot index (LME), gold bullion spot index (LBM), London palladium free market spot index, London platinum free market spot index and silver spot index (LBM). The empirical market data of daily prices and daily volumes utilized in this study are obtained from datastream international. Moreover, the actual research horizon for each index, which referred to Table 1, is trimmed according the data availability from datastream international. Meanwhile, the whole universal set of trading rules are employed in the futures markets while only part of them are tested in the spot markets due to the lack of volume data in the latter. Ultimately, the trading rules for the futures and spot markets are respectively amounting to 7846 and 5806.

The summary statistics of the daily returns for ten precious metal market indices are reported in Table 1. Among them, the longest research coverage belongs to gold bullion spot index (LBM) with 10947 observations and the shortest for copper, grade a cash spot index (LME) with 4296 observations. The mean daily return is rather diversified ranging from the highest 0.031 of gold bullion spot index (LBM) to the lowest 0.0168 of silver 5000 OZ futures index (CMX). The highest volatility is found in the silver spot index (LBM) of 0.0224 and the lowest volatility is found in the gold 100 OZ futures index (CMX) of 0.0124. The empirical evidence shows that most markets possess left skewness even not in the statistical significance. However, the fat right tails are strongly embedded in all precious metal markets as indicated in Table 1 and, therefore, the behaviors of daily returns are almost far from the presumed normality assumption. Finally, the autocorrelation statistics shown in Table 1 indicate the palladium futures and spots exhibit strong positive first order autocorrelation while other markets show no significant series dependence for the time lags structure.

Table 1. Summary statistics of the precious metal market futures and spot indices

	Data period	No. of observations	Variables[b]							
			Mean (%)	S.D.	Skewness	Kurtosis	$\rho(1)$	$\rho(2)$	$\rho(3)$	$\rho(4)$
High grade copper futures index (CMX)	1989/09~2009/12	5295	0.0170	0.0170	-0.2067	7.4541	-0.0772	-0.0009	-0.0117	0.0124
Gold 100 OZ futures index (CMX)	1977/08~2009/12	8428	0.0230	0.0124	-0.0560	10.7629	-0.0116	0.0156	0.0195	-0.0398
Palladium futures index (NYM)	1979/01~2009/12	8078	0.0203	0.0205	-0.0829	10.7163	0.0635***	0.0020	-0.0088	-0.0014
Platinum futures index (NYM)	1979/01~2009/12	8078	0.0174	0.0168	-0.1772	11.7924	0.0073	0.0267**	0.0172	-0.0322
Silver 5000 OZ futures index (CMX)	1988/05~2009/12	5629	0.0167	0.0170	-0.6048	10.8871	-0.0123	0.0038	0.0090	-0.0186
Copper, grade a cash spot index (LME)	1993/07~2009/12	4296	0.0296	0.0172	-0.2000	7.0332	-0.0606	-0.0433	0.0070	0.0202
Gold bullion spot index (LBM)	1968/01~2009/12	10947	0.0315	0.0128	0.2164	31.4141	-0.0307	0.0103	0.0121	0.0033
London palladium free market spot index	1987/01~2009/12	5989	0.0188	0.0198	-0.1431	10.9003	0.0442***	-0.0379	-0.0189	-0.0043
London platinum free market spot index	1976/01~2009/12	8860	0.0257	0.0168	-0.4670	12.6317	-0.0087	-0.0189	0.0203	-0.0222
Silver spot index (LBM)	1970/01~2009/12	10422	0.0215	0.0224	0.2314	42.4664	-0.1221	0.0163	0.0140	-0.0075

Notes: [b] $\rho(i)$ is the estimated autocorrelation at lag i for each series. * Significant of the two-tailed test at the 10% level. ** Significance at the 5% level. *** Significant at the 1% level.

2.1. Optimum rules for the thirteen precious metal market indices. This Section reports the characteristics of the best trading rules and their associated profits within the precious metal market indices. With no consideration of the issues of non-synchronous trading biases or transaction costs, the optimal trading rules for the spot markets and futures markets are rather distinct. The OBV rules and MA rules are respectively served as the best in futures and spot markets. Among the best MA rules in futures and spot markets, the windows of moving averages are diversified, ranging two- through 250-day, which contrast sharply with about two- through five-day windows reported in U.S. markets by Sullivan et al. (1999) and in Asian markets by Chen et al. (2009). In consequence, the resultant trading signals for precious metal market indices tend to be diversified. From these, the lowest frequency is found in the high grade copper futures index (CMX) and gold 100 OZ futures index (CMX), where the total number of buy and sell signals are 16 and 15. The highest frequency is found in the palladium futures index (NYM), where the total number of buy and sell signals are 1791 and 1790. Moreover, almost all best trading rules exhibit significant mean returns at 1% level except silver 5000 OZ futures index (CMX) and silver spot index (LBM) reaching 5% significance. The mean daily returns of the best rules range from a high of 0.146% for the London palladium free market spot index to a low of 0.043% for gold 100 OZ futures index (CMX); all of these easily outperform a buy-and-hold strategy across their various market indices.

We further decompose the results on trading signals into buy-signals and sell-signals in order to examine, in some detail, the characteristic features of these buy and sell signals, and find that the frequency of buy and sell signals is approximately equal for each market. For instance, London palladium free market spot index results in a total of 1380 (1379) buy (sell) signals for the best rules. However, the frequency of buy and sell signals varies across the different markets. For example, palladium has the highest of buy and sell signals, whether in the futures (1791:1790) and spot (1380:1379) market, whereas gold has the lowest buy and sell signals in the futures (16:15) and spot (17:16) market. As a result, there are also significant variations in the ratios of the average holding horizons for buy and sell signals across markets. It is found to be highest in the gold bullion spot index (LBM) with a ratio of 379.18:265.63, and lowest in the London palladium free market spot index, where the ratio is 2.36:1.80.

As noted by Bessembinder and Chan (1995), significant return differentials between buy and sell signals indicate that the technical rules in precious metal market indices are capable of conveying economic information. The differentials in the daily returns resulting from buy and sell signals for the best rules found in this study are sufficiently wide to generate significant economic profits across the precious metal market indices. For example, the mean difference between buy and sell signals in the London palladium free market spot index 0.285%, whilst the gold 100 OZ futures index (CMX), which has the lowest figure, still manages to achieve a 0.079% return differential.

2.2. The effects of data snooping on trading rules. We examine the profitability of technical analysis in greater depth in this section by taking into account the level of dependence that exists between the trading models, adjusting for data snooping bias by employing the White (2000) "reality check" and the Hansen (2005) "superior predictive ability" test.

As shown in Table 3, the mean daily return of the best rule in ten precious metal market indices all are significantly higher than the buy-and-hold mean daily returns. The notable examples include London palladium free market spot index, palladium futures index (NYM), copper, grade a cash spot index (LME), and gold bullion spot index (LBM) respectively amounting to 36.38%, 35.16%, 25.93%, and 14.42% comparing to 4.7%, 5.07%, 7.40%, and 7.87% of the indices in annual returns. All the four precious metal future and spot indices above provide abnormal returns significantly in terms of nominal reality check. However, only London palladium free market spot index and palladium futures index (NYM) are marginally better than the market indices in the SPA test and RC test. The fact clearly delineates the tendency of over-optimism toward the acceptance of superior trading rules as well as the neglect of the potential data snooping effect among the universe of technical analysis. Table 3 shows that, as in the majority of prior empirical studies within the finance literature, all of the best rules in the precious metal market indices significantly outperform their buy-and-hold alternatives. However, our empirical results also reveal quite a striking finding in precious metal markets, that when controlling for the dependence in the trading models of the Sullivan et al. (1999) "universe", most of the precious metal market indices in our sample, with the two exceptions of London palladium free market spot index and palladium futures index (NYM), confirm the non-existence of a superior technical rule.

Table 2. Standard test results for the technical rules among the precious metal market futures and spot indices

	Best rule[a]	Order[b]	Mean		Long day[c] /buy signals		Buy return[d]		Short day[c] / sell signals		Sell return[d]		BAHD[e] /SAHD		Buy-Sell[d]		Round-trip cost[f]
			(%)	t-value			(%)	t-value			(%)	t-value			(%)	t-value	(%)
High grade copper futures index (CMX)	MA(40, 125, 0, 0, 50)	2495	0.073	3.066	2694	16	0.098	3.129	2350	15	0.045	3.129	168.38	156.67	0.142	2.982	0.505
Gold 100 OZ futures index (CMX)	MA(30, 250, 0, 0, 25)	2425	0.043	3.098	4677	16	0.061	3.167	3500	15	0.018	3.167	292.31	233.33	0.079	2.838	0.168
Palladium futures index (NYM)	MA(1, 2, 0, 0, 0)	498	0.141	6.082	4427	1791	0.151	4.963	3400	1790	0.126	4.963	2.47	1.90	0.278	5.957	0.329
Platinum Futures Index(NYM)	MA(50, 125, 0, 0, 50)	2496	0.048	2.563	4477	27	0.064	2.546	3350	26	0.028	2.546	165.81	128.85	0.091	2.398	0.119
Silver 5000 OZ futures index (CMX)	OVB(20, 25, 0, 3, 0)	7066	0.053	2.268	2697	583	0.088	2.736	2679	584	0.018	2.736	4.63	4.59	0.105	2.264	0.104
Copper, grade a cash spot index (LME)	MA(10, 75, 0, 0, 5)	2156	0.104	3.812	2380	29	0.123	3.605	1665	28	0.076	3.605	82.07	59.46	0.200	3.610	0.022
Gold bullion spot index (LBM)	MA(30, 250, 0, 0, 25)	2425	0.058	4.611	6446	17	0.081	4.655	4250	16	0.024	4.655	379.18	265.63	0.104	4.077	0.206
London palladium free market spot index	MA(1, 2, 0, 0, 0)	498	0.146	5.558	3256	1380	0.163	4.783	2482	1379	0.122	4.783	2.36	1.80	0.285	5.396	0.288
London platinum free market spot index	MA(100, 125, 0, 0, 25)	2393	0.052	2.850	4960	30	0.080	3.332	3649	30	0.013	3.332	165.33	121.63	0.093	2.547	0.127
Silver spot index (LBM)	MA(2, 30, 0, 0, 50)	2448	0.051	2.263	5521	47	0.092	2.821	4650	46	0.003	2.821	117.47	101.09	0.095	2.088	0.105

Notes: [a]"Best rule MA" denotes the moving average with five parameters (*n*, *m*, *b*, *d*, *c*), where *n*-days is the short-term horizon line; *m*-days is the long-term horizon line; *b* is the filter rate (%); *d*-days is the time delay; and *c*-days is the holding days. [b]"Order" refers to the location of the best universal rule. [c]"Long (short) day" refers to the number of buying days for the best rule. [d]"Buy (sell) signals" referring to the number of buy (sell) signals for the best rule with the t-values referring to the two-tailed t-test. [e]"BAHD (SAHD)" denotes the average holding days for the buy (sell) signals. [f]The transaction (round-trip) costs for thirteen precious metal market indices are adopted from member fees of CME group.

Table 3. Bootstrapped test results for the technical rules among the precious metal market futures and spot indices

	Best rule[a]	Order[b]	Daily return[c] (%)	Daily return[c] t-value	Annual return (%)	Index (%)	SPA[d]	RC[e]	Nominal RC[f]
High grade copper futures index (CMX)	MA(40, 125, 0, 0, 50)	2495	0.073	3.066	18.266	4.252	0.886	0.886	0.112
Gold 100 OZ futures index (CMX)	MA(30, 250, 0, 0, 25)	2425	0.043	3.098	10.639	5.753	0.954	0.996	0.188
Palladium futures index (NYM)	MA(1, 2, 0, 0, 0)	498	0.141	6.082	35.161	5.073	0.092	0.092	0.000
Platinum futures index (NYM)	MA(50, 125, 0, 0, 50)	2496	0.048	2.563	12.083	4.355	0.940	0.986	0.172
Silver 5000 OZ futures index (CMX)	OBV(20, 25, 0, 3, 0)	7066	0.053	2.268	13.163	4.180	0.998	1.000	0.316
Copper, grade a cash spot index (LME)	MA(10, 75, 0, 0, 5)	2156	0.104	3.812	25.934	7.404	0.586	0.590	0.034
Gold bullion spot index (LBM)	MA(30, 250, 0, 0, 25)	2425	0.058	4.611	14.424	7.871	0.638	0.900	0.084
London palladium free market spot index	MA(1, 2, 0, 0, 0)	498	0.146	5.558	36.382	4.705	0.080	0.086	0.002
London platinum free market spot index	MA(100, 125, 0, 0, 25)	2393	0.052	2.850	12.901	6.422	0.976	1.000	0.312
Silver spot index (LBM)	MA(2, 30, 0, 0, 50)	2448	0.051	2.263	12.834	5.378	0.984	1.000	0.450

Note: [a]"Best rule MA"denotes the moving average with five parameters (*n*, *m*, *b*, *d*, *c*), where *n*-days is the short-term horizon line; *m*-days is the long-term horizon line; *b* is the filter rate (%); *d*-days is the time delay; and *c*-days are the holding days. [b]"Order" refers to the location of the best universal rule. [c]The *t*-value refers to the two-tailed *t*-test. [d]"RC" refers to the p-value for the White (2000) 'reality check' to the full universe. [e]"SPA" refers to the p-value for the Hansen (2005) 'superior predictive ability' test to the full universe. [f]"Nominal RC" refers to the p-value obtained by applying the "reality check" to the best rule only, without relating it to the full set of rules.

2.3. The effects of non-synchronous trading bias on technical analysis. Technical analysis trading profits arise mainly from positive serial dependence on stock index returns. However, as demonstrated by Scholes and Williams (1977), non-synchronous trading amongst component stocks may give rise to spurious positive serial dependence in the index returns, leading to the resultant measurement error potentially overestimating the trading profits of technical analysis.

We adopt the one-day lag adjustment proposed by Bessembinder and Chan (1995) in the present study to partially calibrate the non-synchronous bias. Specifically, we associate the day $t + 2$ return with the initial trading signal emitted at the close of day t, thereby, allowing the component stocks of the index to be fully traded on the intervening days. Our empirical results, which are reported in Table 4, reveal that the non-synchronous effect is considerable and results in a significant alteration to the best rules selected for the samples.

After calibrating the non-synchronous bias, we can find the best rules still lie in the original rule categories except high grade copper futures index (CMX) changing from the MA rule to the OBV rule. However, the parameter structures of best rules indeed move slightly around the original ones. For example, the best rule in palladium futures index (NYM) changes from MA (1, 2, 0, 0, 0) to MA (1, 250, 0, 0, 10). Furthermore, controlling for the non-synchronous effect is also found to have adverse effects on the performance of the best rules reported in Table 3. For instance, the highest mean return for the London palladium free market spot index in Table 3, which is achieved by the MA (1, 2, 0, 0, 0) rule, declines from 0.15% to 0.01% when taking the non-synchronous effect into account, whilst the new optimal rule, MA (50, 100, 0.001, 0, 0), mean daily return is 0.10%, the gap between the two best rules is obvious. In fact, the effect of non-synchronous has much change for the best trading rules but the mean daily returns are not significantly affected. The nominal RC test provides the same result to Table 3 that only four previous indices, namely London palladium free market spot index, palladium futures index (NYM), copper, grade a cash spot index (LME), and gold bullion spot index (LBM), remain significantly better than the buy-and-hold strategy.

We also take the model dependence into consideration by carrying out the reality check and superior predictive ability test. As shown in Table 4, when ignoring the potential model dependence in the Sullivan et al. (1999) "universe" of technical analysis, only four indices which are the same with Table 3 are still superior, in terms of the "nominal reality check". However, the picture is rather different after controlling for the data snooping effect, there are no indices which have the best rule through the reality check and the superior predictive ability test. The evidence presented in Table 4 provides support for Sullivan et al. (1999) and White (2000) on the need for bootstrap testing when assessing the performance of technical analysis. The evidence also reinforces the fact that data snooping has a potentially serious bias when assessing the profitability of technical analysis rules.

Table 4. Bootstrapped test results for the technical rules among the precious metal market futures and spot indices with non-synchronous adjustment

	Best rule[a]	Order[c]	Daily return		Old best rule return[b]		SPA[d]	RC[e]	Nominal RC[f]
			(%)	t-value	(%)	t-value			
High grade copper futures index (CMX)	OBV(30, 100, 0.005, 0, 0)	6203	0.074	3.092	0.068	2.852	0.824	0.900	0.104
Gold 100 OZ futures index (CMX)	MA(40, 250, 0, 0, 25)	2426	0.041	3.013	0.041	2.951	0.980	1.000	0.198
Palladium futures index (NYM)	MA(1, 250, 0, 0, 10)	2087	0.090	3.892	0.012	0.523	0.574	0.748	0.022
Platinum futures index (NYM)	MA(40, 125, 0, 0, 50)	2495	0.045	2.365	0.043	2.283	0.950	0.992	0.196
Silver 5000 OZ futures index (CMX)	OBV(10, 25, 0, 0, 25)	7649	0.050	2.158	0.043	1.868	1.000	1.000	0.338
Copper, grade a cash spot index (LME)	MA(10, 75, 0, 2, 0)	1676	0.098	3.607	0.087	3.180	0.636	0.648	0.056
Gold bullion spot index (LBM)	MA(40, 250, 0, 0, 25)	2426	0.056	4.485	0.056	4.460	0.728	0.932	0.094
London palladium free market spot index	MA(50, 100, 0.001, 0, 0)	791	0.101	3.849	0.009	0.338	0.498	0.562	0.038
London platinum free market spot index	MA(100, 125, 0, 5, 0)	2018	0.055	3.020	0.049	2.720	0.940	0.996	0.274
Silver spot index (LBM)	MA(1, 5, 0, 0, 0)	499	0.059	2.580	0.057	2.533	0.992	1.000	0.348

Note: [a]"Best rule MA" denotes the moving average with five parameters (*n*, *m*, *b*, *d*, *c*), where *n*-days is the short-term horizon line; *m*-days is the long-term horizon line; *b* is the filter rate (%); *d*-days is the time delay; and *c*-days are the holding days. [b]"Old best rule return" refers to the return of the best rule without institutional adjustments, as indicated in Table 2. [c]"Order" refers to the location of the best universal rule. [d]"RC" refers to the p-value for the White (2000) "reality check" to the full universe. [e]"SPA" refers to the p-value for the Hansen (2005) "superior predictive ability" test to the full universe. [f]"Nominal RC" refers to the p-value obtained by applying the "reality check" to the best rule only, without relating it to the full set of rules.

2.4. The effects of transaction costs on technical analysis. It has been argued by many researchers that transaction costs are a critical element in the overall appraisal of the economic significance of trading rules, particularly with regard to those rules which tend to generate frequent trades. We incorporate the transaction costs of the ten precious metal market indices into the analysis of the profitability of technical analysis in this study. The round-trip costs, utilized in this study, are drawn from the member fees of CME group and range from the highest high grade copper futures index (CMX) of 0.5% to the lowest copper, grade a cash spot index (LME) of 0.02%, the details referred to Table 2.

When considering transaction costs, the best rules is similar with Table 3 which with no consideration of the issues of non-synchronous trading biases or transaction costs. In particular, as shown in Table 5, the best rules of Palladium indices in the future and spot market regularly switch to the long-run strategies in order to avoid the frequently traded rules which attract high transaction costs. We also find that transaction costs exert great impacts on the profitability of technical analysis and results in the highest mean daily return (0.103%) to copper, grade a cash spot index (LME) which have the lowest transaction cost (0.02%).

We go on to further explore the effects of data snooping bias under a setting in which transaction costs are taken into consideration. Even in the nominal sense of the reality check, the trading rules in only four of the ten precious metal market indices (London palladium free market spot index, palladium futures index (NYM), copper, grade a cash spot index (LME), and gold bullion spot index (LBM)) continue to exhibit superior profitability, as compared to their corresponding buy-and-hold strategy. However, the picture is rather different after controlling for the data snooping effect, no indices which have the best rule, through the reality check and the superior predictive ability test. The finding arrogantly maintains the assertion of efficient market hypothesis among ten more developed precious metal markets under examination.

Table 5. Bootstrapped test results for the technical rules amongst the precious metal market futures and spot indices with transaction costs adjustment

	Best rule[a]	Order[c]	Daily return		Old best rule return[b]		SPA[d]	RC[e]	Nominal RC[f]
			(%)	t-value	(%)	t-value			
High grade copper futures index (CMX)	MA(40, 125, 0, 0, 50)	2495	0.070	2.941	0.070	2.941	0.916	0.954	0.122
Gold 100 OZ futures index (CMX)	MA(30, 250, 0, 0, 25)	2425	0.042	3.054	0.042	3.054	0.954	0.996	0.170
Palladium futures index (NYM)	MA(1, 250, 0, 0, 10)	2087	0.088	3.798	-0.010	-0.427	0.672	0.736	0.028
Platinum futures index (NYM)	MA(50, 125, 0, 0, 50)	2496	0.048	2.521	0.048	2.521	0.928	0.982	0.116
Silver 5000 OZ futures index (CMX)	OBV(10, 25, 0, 0, 25)	7649	0.044	1.886	0.030	1.293	1.000	1.000	0.386
Copper, grade a cash spot index (LME)	MA(10, 75, 0, 0, 5)	2156	0.103	3.801	0.103	3.801	0.578	0.578	0.066
Gold bullion spot index (LBM)	MA(30, 250, 0, 0, 25)	2425	0.057	4.562	0.057	4.562	0.636	0.912	0.076

Table 5 (cont.). Bootstrapped test results for the technical rules amongst the precious metal market futures and spot indices with transaction costs adjustment

	Best rule[a]	Order[c]	Daily return		Old best rule return[b]		SPA[d]	RC[e]	Nominal RC[f]
			(%)	t-value	(%)	t-value			
London palladium free market spot index	MA(50, 100, 0, 0, 0)	566	0.101	3.851	0.007	0.274	0.554	0.618	0.034
London platinum free market spot index	MA(100, 125, 0, 0, 25)	2393	0.051	2.802	0.051	2.802	0.964	0.990	0.340
Silver spot index (LBM)	MA(2, 30, 0, 0, 50)	2448	0.050	2.221	0.050	2.221	0.996	1.000	0.496

Notes: [a]"Best rule MA" denotes the moving average with five parameters (*n*, *m*, *b*, *d*, *c*), where *n*-days is the short-term horizon line; *m*-days is the long-term horizon line; *b* is the filter rate (%); *d*-days is the time delay; and *c*-days are the holding days. [b]"Old best rule return" refers to the return of the best rule without institutional adjustments, as indicated in Table 2. [c]"Order" refers to the location of the best universal rule. [d]"RC" refers to the p-value for the White (2000) "reality check" to the full universe. [e]"SPA" refers to the p-value for the Hansen (2005) 'superior predictive ability' test to the full universe. [f]"Nominal RC" refers to the p-value obtained by applying the "reality check" to the best rule only, without relating it to the full set of rules.

Conclusions

We carry out a detailed investigation in this study of the profitability of technical analysis amongst ten precious metal market indices over the period of 1968-2009. We employ the bootstrap results of the White (2000) "reality check" and the Hansen (2005) "superior predictive ability" test in order to determine whether any profitable trading rule exists, drawing from the "universe" of technical strategies proposed by Sullivan et al. (1999). Our empirical findings first indicate that, when non-synchronous trading bias and transaction costs are ignored, the best strategies in our sample are provided by short-window "moving averages" rules, which are Palladium futures index (NYM) (1, 2, 0, 0, 0) and London palladium free market spot index (1, 2, 0, 0, 0). The accompanying profits of these rules are significant according to the traditional test employed by Brock et al. (1992) and Bessembinder and Chan (1995). Furthermore, the results, remain valid in, are palladium futures index (NYM) and London palladium free market spot index, even after controlling for data snooping bias through the bootstrap reality check and superior predictive ability test.

Second, we find that when a one-day lag scheme is implemented to account for non-synchronous trading bias, there are changes in the optimal trading rules, but they are similar in trading profits. Furthermore, there is different result with ignoring non-synchronous trading bias, no indices through the bootstrap tests in both the White (2000) reality check and the Hansen (2005) superior predictive ability test. Third, when transaction costs are taken into account, there entails a similar effect in trading profits as non-synchronous adjustment dose. As a result, both, the reality check and the superior predictive ability test, reject the existence of economically profitable rules in all of the precious metal market indices. The empirical evidence seems suggest the relative magnitude of noises surrounding the true efficacy of technical analysis rank most from data snooping and the next from both non-synchronous trading and transaction costs.

This study brings together powerful bootstrap tests, along with two institutional adjustments (non-synchronous trading and transaction costs) to ascertain the profitability of technical analysis in ten precious metal market indices. The empirical results indicate that these adjustments have an enormous impact on the performance of the technical analysis rules. Indeed, our results clearly show that economic profits are unlikely to be earned from the use of technical analysis within these particular markets.

References

1. Arnold, C.M. (1993). Timing the market: how to profit in bull and bear markets with technical analysis, Chicago: Probus Publishing Company.
2. Bessembinder, H., & Chan, K. (1995). The profitability of technical trading rules in the Asian stock markets, *Pacific-Basin Financial Journal*, 3, pp. 257-284.
3. Blume, L., Easley, D., O'Hara, M. (1994). Market statistics and technical analysis: the role of volume, *Journal of Finance*, 49, pp. 153-183.
4. Brock, W., Lakonishok, J., & Lebaron, B. (1992) Simple technical trading rules and the stochastic properties of stock returns, *Journal of Finance*, 47, pp. 1731-1764.
5. Cheng, C.W., Huang, C.S., and Lai, H.W. (2009). The impact of data snooping on the testing of technical analysis: an empirical study of Asian stock markets, *Journal of Asian Economics*, 20 (5), pp. 580-591.
6. Diebold, F.X., and Mariano, R.S. (1995). Comparing predictive accuracy, *Journal of Business and Economic Statistics*, 13, pp. 253-265.
7. Fama, E.F., & Blume, M.E. (1970). Efficient capital markets: a review of the theory and empirical work, *Journal of Finance*, 25, pp. 383-417.
8. Fama, E.F., and Blume, M. (1966). Filter rules and stock market trading, *Journal of Business*, 39, pp. 226-241.

9. Fifield, S.G.M., Power, D. M., & Sinclair, C.D. (1995). An analysis of trading strategies in eleven European stock markets, *European Journal of Finance*, 11, pp. 531-548.
10. Hansen, P.R. (2005). A test for superior predictive ability, *Journal of Business and Economic Statistics*, 23, pp. 360-380.
11. Hsu, P.H., Hsu, Y.C., Kuan C.M. (2010). Testing the predictive ability of technical analysis using a new stepwise test without data snooping bias, *Journal of Empirical Finance*, 17 (3), pp. 471-484.
12. Jones, J.D. and Uri, N.D. (1990). Market efficiency, spot metals prices and cointegration: evidence for the USA, 1964-1987, Resources Policy, 16 (4), pp. 261-268.
13. Lo, A., & MacKinlay, A.C. (1990). Data snooping biases in tests of financial asset pricing models, *Review of Financial Studies*, 3, pp. 431-467.
14. Lo, A.W., Mamaysky, H., Wang, J. (2000). Foundations of technical analysis: computational algorithms, statistical inference, and empirical implementation, *Journal of Finance*, 55, pp. 1705-1765.
15. MacDonald, R. and Taylor, M. (1988a). Metal prices, efficiency and cointergration: some evidence from the London metal exchange, Bulletin of Economic Research, 40 (3), pp. 235-239.
16. MacDonald, R. and Taylor, M. (1988b). Testing rational expectations and efficiency in the London metal exchange, Oxford Bulletin of Economics & Statistics, 50 (1), pp. 41-52.
17. Murphy, J.J. (1986). Technical analysis of the futures markets, NY: New York Institute of Finance, Prentice-Hall.
18. Narayan, P.K., Narayan, S. and Zheng, X. (2010). Gold and oil futures markets: are markets efficient? Applied Energy.
19. Park, C.H., and Irwin, S.H. (2007). What do we know about the profitability of technical analysis? *Journal of Economic surveys*, 21 (4), pp. 787-826.
20. Politis, D.N., and Romano, J.P. (1994). The stationary bootstrap, *Journal of American Statistical Association*, 89, pp. 1303-1313.
21. Pring, M.J. (2002). Technical analysis explained, New York: McGraw-Hill.
22. Savin, G., Weller, P., Zvingelis, J. (2007). The predictive power of "head-and-shoulders" price patterns in the U.S. stock market, *Journal of Financial Econometrics*, 5, pp. 243-265.
23. Scholes, M., and Williams, J. (1977). Estimating betas from non-synchronous data, *Journal of Financial Economics*, 5, pp. 309-327.
24. Sephton, P.S. and Cochrane, D.K. (1991). The efficiency of the London metal exchange: another look at the evidence, *Applied Economics*, 23 (4), pp. 669-674.
25. Sephton, P.S. and Cochrane, D.K. (1990). A note on the efficiency of the London metal exchange, *Economics Letters*, 32, pp. 341-345.
26. Sullivan, R., Timmermann, A., White, H. (1999). Data snooping, technical trading rule performance and the bootstrap, *Journal of Finance*, 54, pp. 1647-1691.
27. West, K.D. (1996). Asymptotic inference about predictive ability, *Econometrica*, 64, pp. 1067-1084.
28. White, H. (2000). A reality check for data snooping, *Econometrica*, 68, pp. 1097-1126.