**Does intraday technical trading have predictive power in precious metal markets?**

**Abstract**

Previous research has identified that investors place more emphasis on technical analysis than fundamental analysis, however the research has largely been confined to daily data and stock market indices. This paper studies whether intraday technical trading rules have any significant predictive power in the precious metals market through three popular moving average rules. We find that using the standard parameters previously used in the literature, technical trading rules offer no predictive power whatsoever. However after utilising a universe of parameters, we find a number of parameter combinations offer significant predictability in the gold market, but there remains no significant predictability in the silver market. Our results show that the longer parameters of the technical trading rules are more successful than the traditional parameters chosen in the literature. Therefore intraday technical trading rules have some predictive power in the gold market but offer no significant predictability in the silver market.

Keywords: Precious Metals; Technical Analysis; Predictability; Gold; Silver

*JEL classification:* G12; G15

**1. Introduction**

The efficient market hypothesis (EMH) is one of the most studied theories in the finance literature. In its weak-form, stock prices reflect all available information, such that technical analysis trading rules based on historical price data offer no predictive power (Fama 1970). However, trading models based on technical analysis that employ momentum or trend following technology have been found to have significant predictive power (Brock et al.,1992 amongst others).[[1]](#footnote-1) Technical analysis remains very popular among practitioners with Menkhoff (2010) showing that the vast majority of fund managers use technical analysis and it is preferred to fundamental analysis as a market timing and decision making tool. With the introduction of new technology and platforms, investors increasingly trade intraday rather than daily. As Marshall et al (2008) point out, investors have been found to place more emphasis on technical analysis the shorter the forecasting horizon, with investors placing twice as much weight on the technical analysis for intraday horizons as they do for one-year horizons.

Given the increased attention on precious metals and their importance to investors, this study examines the intraday predictability of spot gold and silver at 5-minute intervals using a number of popular technical trading rules. The sample commences in 2008 and ends in 2015 thereby including the effects on these markets of central bank quantitative easing. Gold and silver are two of the most traded assets worldwide, they also play an important role for investors as well as comprising an important asset for central banks.[[2]](#footnote-2) Precious metals are also of paramount interest to investors as the introduction of new capital requirements for banks have enhanced demand for liquid assets in a banks risk management profile, while gold and silver have both been found to be safe havens, even at different times (Lucey and Li 2015).

Precious metals are easily traded and have the advantage of being priced in a common currency, so are not subject to bias that may be associated with index construction and variation that may affect studies involving stock indices. Our approach is straight forward and follows other work such as Brock et al. 1992. Initially, we examine the various time series using simple, exponential and weighted moving average rules to determine whether these trading rules have any predictive power. We use the most popular parameters of these technical trading rules from studies of daily data and study their performance, although there is no reasonable rationale why investors would choose a certain set of parameters or follow the same set of parameters for daily data when analysing intraday data. Therefore we also run a parameter sweep where we study all possible combinations of the parameters of the rules. This provides a detailed analysis of the full performance of these technical trading rules over the sample period.

Nevertheless, any significant predictability found will be susceptible to the data-mining fallacy as noted by Zakamulin (2014). That is, using historical data to test k-trading rules, selecting the rule that performs best and then either explicitly or implicitly assuming that the expected future performance of this rule will be the same as the past performance. To avoid this, we run an in- and out-of-sample test to study whether the most successful predictive rules in the in-sample period are successful in the out-of-sample period, we also use the bootstrap methodology of Okunev and White (2003) to examine the robustness of our results.

The contributions of this study are as follows: Firstly no studies to our knowledge explore whether technical analysis has predictive power in spot precious metal markets at high-frequency. While some studies examine the predictive power of precious metals daily spot or daily futures markets, we examine the predictive power of some of the most popular trading rules in gold and silver markets at 5-minute intervals. Secondly after examining the most popular parameters of the technical trading rules for daily data, we conduct a parameter sweep where we study which parameters of the technical trading rules are most predictive. This means that we examine in total 66,297 moving average rules for each market, which is one of the largest set of trading rules studied in the literature. Thirdly we report the average predictive power of the parameters of the technical trading rules, which shows that the longer the horizon, the more successful the technical trading rules become. Finally to avoid the data-mining fallacy, we examine the in- and out-of-sample performance the trading rules to determine whether investors could have had some rationale to trade on the successful parameters of the trading rules. To add further robustness to our results, we use the bootstrap methodology of Okunev and White (2003).

The remainder of the paper is organized as follows. The next section presents the related literature while Section 3 presents the methodology. Section 4 reports the data and Section 5 the empirical results, while Section 6 summarises the findings and provides conclusions.

**2. Literature Review**

Despite the fact that investors have placed more value on short-term technical analysis, the majority of the financial literature has focused on the profitability of technical trading rules using daily data[[3]](#footnote-3) (see for example Brock et al 1992; Hudson et al 1996; Shynkevich 2012; Urquhart et al 2015; Metghalchi et al 2015). Given the availability of financial technology to trade at high frequencies, there has been a lack of studies that examine the predictability of intraday returns from technical trading rules (for some exceptions see Marshall et al 2008; Yamamoto 2012; Duvinage et al 2013; Cervelló-Royo et al 2015). Furthermore, there is a distinct lack of studies examining technical trading rules on precious metals given the increased attention they have received in the literature and the fact that Emmrich and McGroarty (2013) find in favour of including gold in investment portfolios, especially since the financial crisis in 2007.

Technical trading rules have been examined in detail in the literature (see Park and Irwin 2007), the study by Brock, Lakonishok and LeBaron (1992) where they find that technical trading rules have significant predictive power in the DJIA over 90 years is one of the most influential in the early literature. This result led to an explosion of studies scrutinising the results (see for instance Bessembinder and Chan 1998; Sullivan et al 1999; Day and Wang 2002; Ready et al 2002) and studying the performance of technical trading rules in other markets (see for instance Hudson et al 1996; Fifield et al 2005; Manahov et al 2014; Hsu et al 2016; Zarrabi et al 2017). However, recently Fang et al (2013) examined the DJIA and S&P500 out-of-sample data, both pre- and post-dating the original Brock et al (1992) sample and find no evidence of statistical predictability in any of these additional periods. This result was confirmed by Urquhart et al (2015) and as Schulmeister (2009) argues, the profitability of technical trading may have moved from daily to intraday data.

Given the large number of studies examining technical trading rules using daily data, there is a limited but growing literature studying the intraday performance of technical trading rules. Marshall et al (2008) study whether intraday technical analysis is profitable in the US equity market using 7846 popular technical trading rules on 5-minute intervals from January 2002 to December 2003. They find using two bootstrap methodologies that none of the trading rules are profitable after data snooping is taken into account, indicating market efficiency over the 5-min horizon. Schulmeister (2009) examine 2580 technical trading systems from 1960 to 2007 and find that when based on daily data profitability has declined since 1960 and has been absent since the early 1990s. However, when based on 30-minute data the rules are profitable and there is no decline in profitability over time. Yamamoto (2012) examines intraday technical analysis on individual stocks listed on the Nikkei 225. The paper studies 207 stocks after filtering from September 2006 to August 2007 and finds that no strategies beat buy-and-hold within their sample. Duvinage et al (2013) investigate the predictive power of Japanese candlestick rules at 5-minute intervals on data of the 30 constituents of the DJIA index from April 2010 to April 2011. They find that a third of the rules examined outperform the buy-and-hold strategy, but only a few remain profitable once adjusted for transaction costs. Once the data is corrected for data snooping, they find that no rules outperform the buy-and-hold strategy, thus concluding that the predictive power of Japanese candlesticks is too limited for use in active portfolio management. Narayan et al (2015) examine whether exchange rate momentum trading strategies applied to high frequency data are profitable in the emerging markets of Brazil, China, India and South Africa. They find that momentum-based trading strategies lead to statistically significant profits in all four exchange rates, the South African Rand is the most profitable and that the profits are maximised during the financial crisis. Recently, Hudson et al (2017) separate technical trading rules into trend-following and mean-reversion rules and show through commodity ETFs that their performances are drastically different depending on the frequency of data employed.

Studies of technical trading rules applied to precious metal markets have been sparse, with Marshall et al (2008b) studying 7000 rules on 15 major commodity futures, finding that some rules are profitable but the majority of rules are not after accounting for data-snooping. Szakmary et al (2010) find that all dual moving average and channel strategies yield positive returns in 22 of 28 commodity futures markets, while Narayan et al (2013) find that investors can make profits in daily commodity spot markets from technical trading rules. Also, Narayan et al (2014) study momentum-based trading strategies in commodity futures markets and rank the commodities based on their profitability using the moving average rules. They then take a long positon in the best performing commodities and a short position in the worst performing commodities and find that they can make significant profits from this trading strategy.

There is a distinct lack of studies examining the intraday predictability of technical trading rules and no studies examining the intraday performance of spot precious metals. This study seeks to fill this gap.

**3. Methodology**

To prevent data snooping bias, Pesaran and Timmerman (1995) state that as far as possible, rules for predicting stock returns should be formulated and estimated without the benefit of hindsight, and thus we only consider rules in which there is no forward-looking bias. Further, following Marshall et al (2008), we include a wide range of different rules to reduce the risk that any given rule’s profitability is due to chance.

*3.1. Moving Average Rules*

A moving average is an average of observations of the level of an index over several consecutive time periods. The standard SMA rule generates buy (sell) signals on which the investor trades. This strategy is expressed as buying (or selling) when the short-period moving average rises above (or falls below) the long-period moving average. Thus buy and sell signals are generated by crossovers of a long moving average (calculated over *L* days) by a short moving average (*S* days, *S* < *L*). The buy signal is generated when the short-period moving average moves higher than the long-period moving average:

|  |  |  |
| --- | --- | --- |
|  |  | (1) |

Where *Pt* is the price at time *t*. Sell signals are generated when the inequality is reversed:

|  |  |  |
| --- | --- | --- |
|  |  | (2) |

A percentage band may be included to reduce the number of signals by eliminating “whiplash” signals when the short and long period moving averages are close[[4]](#footnote-4). A popular SMA rule in the literature is the (1,200), where the short period is one day and the long period is 200 days. However for completeness, three other common variations of the rule are used, namely the (1,50), (1,100), (1,150) and (1,200). The shorter the size of the moving average, the closer it follows the market, and the longer the size of the moving average, the more it smooth’s market fluctuations. Thus a rule with *S* = 1 is very responsive, that is, whenever the actual returns rises above (below) the moving average, the signal is to buy (sell).

We also study two variations of the SMA such as the exponentially-weighted moving average (EMA) rule where more weight is given to more recent observations, and thus the weight of each price change decreases exponentially. The weighting factor in an EMA is based on a smoothing factor generated by the length of the input. The weighted moving average (WMA) rule is similar to the EMA but with linear weighting, that is, the most recent returns get the greatest weighting and each return preceding that gets a small weight in a linear fashion.

**4. Data**

The precious metals data is collected from Thomson Reuters Tick History for the period 1st January 2008 to 10th September 2014 and consists of close prices taken at 5-minute intervals over the trading day. These prices are made by wholesale market practitioners with prices and trades time-stamped as they arise in online trading platforms. To study the high-frequency performance of technical trading rules, it is important to use short enough intervals to capture the high frequency behaviour of the data, but at the same time long enough to avoid undue noise (Goodhart and O’Hara 1997). Andersen (2000) argues that 5-minute intervals are the best compromise between these, and that is also the length we have chosen. The precious metals each trade from Sunday 22.00 to Friday 20.45, with a daily break between 21.00 and 22.00. Following Hol and Koopman (2002), we define the 5-minute return as:

|  |  |  |
| --- | --- | --- |
|  |  | (3) |

where is the return for the intraday period *d* on trading day *t*. Due to data errors, there are occasionally periods with zero prices and incomplete observations. In this case we replace the price with the price from the previous 5-minute period, similar to Marshall et al (2008). Also similar to Alsayed and McGroarty (2014), we filter the data for incorrect quotes and spurious trades such as when the bid price is greater than the ask price, and the bid volume or ask volume equals zero.

We study the period 1st January 2008 to 10th September 2014. This sample period therefore includes the episodes of Quantitative Easing by the US Federal Reserve that began with the purchase of US$600 billion in mortgage backed securities (MBS). Federal Reserve purchase of Treasury notes and MBS peaked in June 2010 at US$2.1 trillion (Fawley and Neely, 2013)[[5]](#footnote-5). These purchases triggered investor interest in precious metals markets while also attracting more attention in the finance literature.

Table 1 presents the summary statistics for our full data set as well as the subperiod. We examine the distribution characteristics using the following statistics: mean, standard deviation, skewness, kurtosis and the Jarque-Bera test for normality As expected both series have a near zero mean, and while a time plot of the series may display time-varying variance, the series itself would appear to be Gaussian white noise. Such as process is both consistent with wek-form market efficiency and so should preclude abnormal returns based on trend following systems.

We also examine the autocorrelation of the two periods using the Ljung-Box (*Q*-stats) test at lags 6, 12 and 24 days, along with the estimated autocorrelation at lags of 1 to 5 days. The mean return of gold is higher than that of silver, while silver is more volatile given the respective standard deviations. Statistically significant kurtosis is present is present in each market which indicates the presence of fat tails in each of the return distributions. Both markets also present negative skewness, which as consequence the JB-statistics reject normality in both markets. Studying the time-series properties, we observe significant negative autocorrelation at the first three lags in both markets and likewise, the Ljung-Box test is significant at 1% at lags 6, 12 and 24. The negative autocorrelation is consistent with a mean reverting return process following a price move following an information shock. Such market movements could provide exploitable market trading (ie buy or sell the asset at time interval 2 or 3 after a negative or positive price move at time zero).

**5. Empirical Results**

*5.1. Predictive Power of Technical Trading Rules*

Table 2 reports the predictive power of the simple moving average (SMA) and exponential moving average (EMA) on 5-minute data of gold.[[6]](#footnote-6) The results in panel A and panel B show that the average return generated by buy signals is negative in every rule studied for the SMA and EMA and the average sell returns are all positive. Most of these are statistically significant indicating returns from buy (sell) are significantly higher (lower) different from zero. The buy-sell differences are all negative, where the vast majority are statistically significant indicating no predictive power of the SMA and EMA in the 5-minute gold data. Table 3 shows the results for the weighted moving average (WMA) rule in the 5-minute gold market and shows that the average buy (sell) return is negative (positive) in each case, of which the vast majority are statistically significant. The buy-sell differences are all negative and statistically significant indicating the lack of predictive power of these moving average rules in the 5-minute gold market.

Table 4 presents the SMA and EMA results for 5-minute silver and shows that the average buy (sell) returns are all negative (positive) and statistically significant indicating that returns from buy (sell) signals would on average generate negative (returns) that are statistically different to zero. All of the buy-sell differences are negative and statistically significant indicating no predictive power of the SMA and EMA in the 5-minute silver market. The WMA rule results are reported in Table 5 and show that returns from buy (sell) signals would on average generate negative (returns) that are statistically different to zero. All of the buy-sell differences are negative and statistically significant indicating no predictive power of the WMA in the 5-minute silver market.

Therefore, our initial results on the high-frequency moving average trading rules on gold and silver, show that there is no predictive power from these rules in either market. These finding is consistent with the return series behaving as a Gaussian white noise process.

*5.2. Parameter Sweep*

In the previous section, we found that popular technical trading rules do not have any predictive power in the high-frequency prices of gold and silver. However we have predetermined the parameters of the technical trading rules due to their popularity in the literature. Nevertheless, these parameters may not optimise the trading rules and so we run a parameter sweep on our trading rules so ensure that the results found in the previous section are robust.[[7]](#footnote-7) Therefore we run the various forms of the moving average rule using parameters from 1-49 for the short-run moving average and 50-500 for the long-run moving average. Therefore we study in total 66297 different moving average rules.

The summary of results[[8]](#footnote-8) is reported in Table 7 where we show that for gold, 56.42%, 56.27% and 32.68% of the SMA, EMA and WMA rules studied generate positive predictability. However 20.15%, 1.30% and 1.91% of these rules generate positive significant predictability, indicating that the SMA is the most successful of the moving average rules, with the EMA and WMA offering very little significant predictability. Similar to the gold results, the silver results show that some of the parameter combinations for the three moving average rules generate positive predictability. However none of the 66297 moving average rules studied generate significant predictability suggesting that the intraday silver market is very efficient with respect to these technical trading rules.

Table 7 also reports the best five rules for each technical trading rule, selected based on the highest buy-sell differences. It is clear that the most successful moving average rules are the ones with longer time-horizons in the short-run moving average and the long-run moving average. For instance the 44-332, 49-259 and 49-498 rules are the most successful for the SMA, EMA and WMA in gold respectively, suggesting that with high-frequency data the moving average periods should be longer than traditionally used in studies that use daily data. This result is confirmed for silver too, where the most popular moving average rule parameters are 45-300, 48-380 and 49-347 for the SMA, EMA and WMA respectively.

To understand how the performance of the technical trading rules depends on the size of the short-run and long-run parameters, we plot the average buy-sell z-statistic for each parameter in Figure 2. We can clearly see that as the short-run parameter and long-run parameter increases, the buy-sell z-statistic increases indicating that these rules work best for longer time-horizons at high-frequency levels. Also it is clear that very few of the short-run or long-run parameters generate on average significant buy-sell z-statistics indicating that only a few parameters guarantee significant predictability on average, no matter what value the other parameter is.

*5.3. In- and out-of-sample testing*

We have shown that the standard parameters given to technical trading rules in the literature fail to generate any significant predictability however using a parameter sweep, we show that some mix of short-run and long-run parameters do give rise to significant predictability. However any significant predictability from the parameter sweep may be due to data-mining and that there would be no rationale for an investor to select those specific parameters in that time period. [[9]](#footnote-9) To examine this, we run an in- and out-of-sample test on our data to select the best performing trading rules in-sample and to determine whether these rules would have been successful out-of-sample. To determine the best performing rules, we select the five rules with the greatest buy-sell z-statistic.

We use the Bai and Perron (2003) structural break test to determine to breakpoint for our in- and out-of-sample testing. We find that the gold breakpoint is at 12:00 on 31st August 2010 and silver breakpoint is at 08:15 1st October 2010, which is consistent with what is observed in Figure 1.

Table 8 reports the five best trading strategies found the in-sample period and the performance of those strategies in the out-of-sample period. The gold results reported in Panel A show that the SMA is again the most successful rule in the in-sample period, with the five best performing rules generating significant predictability. We find that the most successful rules in-sample also generate positive predictability out-of-sample for all the SMA, EMA and WMA rules, however only the SMA rules are statistically significant in the in- and out-of-sample periods.

In some cases, the level of predictability actually increases out-of-sample, although none move from insignificant to significant. Panel B reports the silver results and shows that the best performing SMA, EMA and WMA rules in-sample offer no predictive power out-of-sample. Only 4 of the best 15 rules from the SMA, EMA and WMA rules offer any significant predictability in the in-sample period. However these rules in the out-of-sample period offer negative predictability indicating that investors would have not have gained any positive returns from following the best performing trading rules in the in-sample period in the out-of-sample period. Therefore Table 8 shows that the best SMA, EMA and WMA rules in the in-sample periods for gold do offer some predictability in the out-of-sample period, however the best performing rules for silver in the in-sample period offer no predictability in the out-of-sample period.

For completeness we compute the parameter sweep in the out-of-sample period for gold and silver and again report the best performing rule for the SMA, EMA and WMA, which is reported in Table 9. All the best five rules for the SMA, EMA and WMA for gold offer significant predictability indicating that technical trading rules in the out-of-sample period do offer some value to investors but investors may have no rationale for choosing these successful parameters as they are different to the best performing rules in the in-sample period. Panel B reports the silver results and show that the best five SMA and WMA offer positive but insignificant predictability, while the EMA rules offer no predictability at all. This supports our earlier results that technical trading rules offer very little predictability in the silver market. However again, none of these rules are the best performing rules in the in-sample period so investors would have no rationale to select these parameters.

*5.4. Bootstrap Analysis*

Data snooping is an active concern when studying the predictability of any technical trading rule. To examine the robustness of our results and to judge the statistically significant of our results, we follow the bootstrap approach suggested by Okunev and White (2003) and employed by Narayan et al (2014; 2015). We employ this bootstrap method that randomly selects with replacement for each of the two precious metals. In this way, a new data set is generated while the characteristics of the original data set are retained. The random process of generating data is repeated 1000 times and the bootstrap p-values are the percentage of simulated mean returns that are greater than the actual mean returns. We only report the results from the most popular trading strategies over the full sample and the in- and out-of-sample periods to conserve space.

The results are reported in Table 10 and are consistent with our previous analysis in that rules that were found to generate significant predictability also generate significant predictability according the bootstrap methodology. The full sample gold results for all three rules as well as the gold in-sample SMA rule are statistically significant indicating the significant predictability of these rules. Also all of the best rules in the out-of-sample period are statistically significant supporting our previous analysis. Panel B reports the silver results and again the results support our previous analysis in that only the best rules in the in-sample SMA and EMA generate significant predictability and all other rules in the full sample and out-of-sample periods fails to generate any significant predictability.

**6. Summary and Conclusions**

This paper studies the intraday predictability of intraday technical analysis in the gold and silver spot markets. Prior work in this area has mostly focussed on daily data, and any intraday studies have focused on stock market indices or commodity futures. Specifically, we examine three popular moving average rules on 5-minute gold and silver markets using traditional parameters used in the literature. We also conduct a parameter sweep where we examine all possible combinations of these technical trading rules, thus examining 66,297 different moving average rules. To avoid data-mining, we run a structural break test on each series and study whether the most successful rules in the in-sample period can be used to generate significant predictability in the out-of-sample period.

The initial results show that the SMA, WMA and EMA trading rules generate significant negative predictability using the standard parameters used in the literature in the high-frequency gold and silver markets. This suggests that there is no significant predictive power in technical trading in the precious metal markets. However, our parameter sweep results show that there are a number of parameter combinations that generate significant predictability in the gold market, but none in the silver market.

Further, the best performing rules have much different parameters to the standard ones used the existing literature. Therefore we show that longer run parameters should be incorporated by investors on intraday data than on daily data and that investors may need to employ different parameters when utilising technical analysis on daily and intraday data. In order to examine whether investors could have actually utilised the best performing rules, we perform an in- and out-of-sample test and show that only the SMA rule for gold generates significant predictability in the in-sample as well as the out-of-sample period. All of the other best rules in the in-sample period generate either insignificant or negative predictability in the out-of-sample period. Finally we perform a bootstrap analysis, which confirms our previous findings. Therefore our results demonstrate that intraday technical trading rules have significant predictive power in the gold market but offers no significant predictability in the silver market, while intraday investors need to select different parameters when employing technical analysis than investors who trade on daily data.

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**Table 1:** Summary statistics for both series and the 2008-2014 period. \*\*\*, \*\*, \* indicates statistically significance at the 1%, 5% and 10% levels respectively.

|  |  |  |
| --- | --- | --- |
|  | Gold | Silver |
| N | 500039 | 456835 |
| Mean | 8.01 x 10-5 | 5.35 x 10-5 |
| SD | 0.000833 | 0.001596 |
| Skew | -0.49 | -1.47 |
| Kurt | 88.24\*\*\* | 107.73\*\*\* |
| JB | 1.51 x 108 | 2.09 x 108 |
| *ρ*(1) | -0.062\*\*\* | -0.092\*\*\* |
| *ρ*(2) | -0.010\*\*\* | -0.004\*\*\* |
| *ρ*(3) | -0.008\*\*\* | 0.010\*\*\* |
| *ρ*(4) | -0.001 | 0.003\*\*\* |
| *ρ*(5) | -0.004\*\*\* | -0.007\*\*\* |
| *Q*(6) | 2005.5\*\*\* | 3957.7\*\*\* |
| *Q*(12) | 2012.4\*\*\* | 3988.2\*\*\* |
| *Q*(24) | 2044.3\*\*\* | 4045.9\*\*\* |

**Table 2:** Test Results for the Moving Average Rules for 5-minute gold data over the period 2008-2014. N(Buys) and N(Sells) are the number of buy and sell signals. Buy and Sell refer to the average returns from buy and sell signals with their associated z-statistics. Buy-Sell denotes the average return from the moving average strategy along with the z-statistics. \*\*\*, \*\*, \* indicate significance at 1%, 5% and 10%.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| RULE | N(BUYS) | N(SELLS) | BUY | BUY z-stat | SELL | SELL z-stat | BUY-SELL | BUY-SELL z-stat |
| Panel A: SMA | | | | | | | | |
| 1,50,0 | 255952 | 244037 | -0.001588 | -8.25 | 0.001812 | 8.51 | -0.003420 | -14.49 |
| 1,50,0.5 | 18534 | 20193 | -0.002560 | -4.24 | 0.005898 | 9.73 | -0.008458 | -4.94 |
| 1,50,1 | 3478 | 4561 | -0.001044 | -0.79 | 0.005560 | 4.42 | -0.006604 | -1.22 |
| 1,100,0 | 261143 | 238796 | -0.001215 | -6.44 | 0.001495 | 6.83 | -0.002710 | -11.44 |
| 1,100,0.5 | 36321 | 38116 | -0.001478 | -3.44 | 0.003319 | 7.32 | -0.004797 | -4.70 |
| 1,100,1 | 8557 | 10712 | -0.001076 | -1.27 | 0.002055 | 2.43 | -0.003132 | -1.18 |
| 1,150,0 | 264083 | 235806 | -0.001108 | -5.92 | 0.001407 | 6.39 | -0.002515 | -10.58 |
| 1,150,0.5 | 52509 | 52631 | -0.001518 | -4.18 | 0.002005 | 5.05 | -0.003523 | -4.61 |
| 1,150,1 | 13860 | 16828 | -0.001346 | -1.99 | 0.001071 | 1.52 | -0.002417 | -1.28 |
| 1,200,0 | 264421 | 235418 | -0.001025 | -5.50 | 0.001312 | 5.94 | -0.002337 | -9.83 |
| 1,200,0.5 | 67161 | 64579 | -0.001410 | -4.34 | 0.001642 | 4.50 | -0.003052 | -4.81 |
| 1,200,1 | 19087 | 22780 | -0.001614 | -2.75 | 0.001038 | 1.71 | -0.002653 | -1.82 |
| Panel B: EMA | | | | | | | | |
| RULE | N(BUYS) | N(SELLS) | BUY | BUY z-stat | SELL | SELL z-stat | BUY-SELL | BUY-SELL z-stat |
| 1,50,0 | 261656 | 238333 | -0.001698 | -8.85 | 0.002033 | 9.42 | -0.003731 | -15.73 |
| 1,50,0.5 | 13384 | 15541 | -0.002477 | -3.51 | 0.005809 | 8.45 | -0.008286 | -3.85 |
| 1,50,1 | 2257 | 2980 | -0.006788 | -3.91 | 0.009878 | 6.40 | -0.016665 | -2.24 |
| 1,100,0 | 263955 | 235984 | -0.001401 | -7.39 | 0.001735 | 7.96 | -0.003136 | -13.20 |
| 1,100,0.5 | 27883 | 30506 | -0.002144 | -4.34 | 0.003247 | 6.45 | -0.005391 | -4.37 |
| 1,100,1 | 5715 | 7904 | -0.001878 | -1.77 | 0.002701 | 2.78 | -0.004579 | -1.28 |
| 1,150,0 | 265709 | 234180 | -0.001171 | -6.25 | 0.001496 | 6.80 | -0.002667 | -11.21 |
| 1,150,0.5 | 41810 | 43417 | -0.001754 | -4.32 | 0.002046 | 4.72 | -0.003800 | -4.19 |
| 1,150,1 | 9517 | 12711 | -0.001360 | -1.67 | 0.000907 | 1.11 | -0.002267 | -0.92 |
| 1,200,0 | 266779 | 233060 | -0.001046 | -5.62 | 0.001359 | 6.14 | -0.002404 | -10.09 |
| 1,200,0.5 | 55038 | 54302 | -0.001209 | -3.44 | 0.001580 | 4.00 | -0.002790 | -3.77 |
| 1,200,1 | 13630 | 17419 | -0.001706 | -2.46 | 0.001060 | 1.53 | -0.002766 | -1.47 |

**Table 3:** Test Results for the WMA for 5-minute gold data over the period 2008-2014. N(Buys) and N(Sells) are the number of buy and sell signals. Buy and Sell refer to the average returns from buy and sell signals with their associated z-statistics. Buy-Sell denotes the average return from the moving average strategy along with the z-statistics. \*\*\*, \*\*, \* indicate significance at 1%, 5% and 10%.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| RULE | N(BUYS) | N(SELLS) | BUY | BUY z-stat | SELL | SELL z-stat | BUY-SELL | BUY-SELL z-stat |
| 1,50,0 | 255492 | 239400 | -0.001710 | -8.84 | -0.002005 | 9.30 | -0.003715 | -15.58 |
| 1,50,0.5 | 10481 | 12093 | -0.004474 | -5.54 | 0.008710 | 11.26 | -0.013184 | -5.08 |
| 1,50,1 | 1653 | 2164 | -0.003706 | -1.85 | 0.016341 | 9.07 | -0.020047 | -2.07 |
| 1,100,0 | 260651 | 237975 | -0.001490 | -7.80 | 0.001796 | 8.28 | -0.003286 | -13.83 |
| 1,100,0.5 | 22394 | 24409 | -0.002010 | -3.67 | 0.004034 | 7.25 | -0.006044 | -4.12 |
| 1,100,1 | 4435 | 5869 | -0.002024 | -1.67 | 0.004337 | 3.90 | -0.006361 | -1.43 |
| 1,150,0 | 262885 | 236579 | -0.001320 | -6.97 | 0.001631 | 7.47 | -0.002951 | -12.42 |
| 1,150,0.5 | 33179 | 35344 | -0.001491 | -3.33 | 0.003246 | 6.91 | -0.004738 | -4.35 |
| 1,150,1 | 7452 | 9573 | -0.001382 | -1.50 | 0.002356 | 2.65 | -0.003739 | -1.26 |
| 1,200,0 | 264518 | 235273 | -0.001207 | -6.41 | 0.001518 | 6.93 | -0.002726 | -11.46 |
| 1,200,0.5 | 43496 | 44790 | -0.001651 | -4.15 | 0.002137 | 5.02 | -0.003788 | -4.30 |
| 1,200,1 | 10509 | 13420 | -0.000920 | -1.21 | 0.000972 | 1.23 | -0.001892 | -0.84 |

**Table 4:** Test Results for the Moving Average Rules for 5-minute silver data over the period 2008-2014. N(Buys) and N(Sells) are the number of buy and sell signals. Buy and Sell refer to the average returns from buy and sell signals with their associated z-statistics. Buy-Sell denotes the average return from the moving average strategy along with the z-statistics. \*\*\*, \*\*, \* indicate significance at 1%, 5% and 10%.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| RULE | N(BUYS) | N(SELLS) | BUY | BUY z-stat | SELL | SELL z-stat | BUY-SELL | BUY-SELL z-stat |
| Panel A: SMA | | | | | | | | |
| 1,50,0 | 231904 | 224881 | -0.005355 | -13.29 | 0.005631 | 13.57 | -0.010986 | -23.21 |
| 1,50,0.5 | 51068 | 48923 | -0.005698 | -7.72 | 0.007352 | 9.61 | -0.013050 | -8.61 |
| 1,50,1 | 15102 | 15826 | -0.006158 | -4.71 | 0.007473 | 5.75 | -0.013631 | -3.76 |
| 1,100,0 | 234531 | 222204 | -0.003566 | -8.93 | 0.003871 | 9.25 | -0.007438 | -15.68 |
| 1,100,0.5 | 83239 | 78001 | -0.004410 | -7.42 | 0.005222 | 8.36 | -0.009632 | -9.27 |
| 1,100,1 | 31047 | 31260 | -0.004570 | -4.94 | 0.006886 | 7.33 | -0.011455 | -5.47 |
| 1,150,0 | 236698 | 219987 | -0.002902 | -7.31 | 0.003227 | 7.67 | -0.006129 | -12.89 |
| 1,150,0.5 | 105546 | 97066 | -0.003299 | -6.14 | 0.004457 | 7.81 | -0.007756 | -8.93 |
| 1,150,1 | 45975 | 44756 | -0.004357 | -5.64 | 0.004850 | 6.07 | -0.009207 | -5.95 |
| 1,200,0 | 237966 | 218669 | -0.002310 | -5.85 | 0.002616 | 6.19 | -0.004926 | -10.35 |
| 1,200,0.5 | 122092 | 111205 | -0.002791 | -5.52 | 0.003759 | 6.95 | -0.006550 | -8.48 |
| 1,200,1 | 60140 | 56904 | -0.002700 | -3.97 | 0.003881 | 5.40 | -0.006581 | -5.19 |
| Panel B: EMA | | | | | | | | |
| RULE | N(BUYS) | N(SELLS) | BUY | BUY z-stat | SELL | SELL z-stat | BUY-SELL | BUY-SELL z-stat |
| 1,50,0 | 233387 | 223398 | -0.006104 | -15.17 | 0.006487 | 15.62 | -0.012591 | -26.56 |
| 1,50,0.5 | 40738 | 40025 | -0.006420 | -7.85 | 0.007494 | 8.95 | -0.013914 | -7.79 |
| 1,50,1 | 10326 | 11867 | -0.007511 | -4.76 | 0.007352 | 4.92 | -0.014863 | -3.18 |
| 1,100,0 | 236448 | 220287 | -0.004120 | -10.32 | 0.004530 | 10.82 | -0.008649 | -18.20 |
| 1,100,0.5 | 71255 | 66774 | -0.004962 | -7.80 | 0.006220 | 9.33 | -0.011182 | -9.53 |
| 1,100,1 | 23104 | 24699 | -0.004344 | -4.09 | 0.005813 | 5.53 | -0.010157 | -4.02 |
| 1,150,0 | 237830 | 218855 | -0.003353 | -8.43 | 0.003748 | 8.91 | -0.007101 | -14.92 |
| 1,150,0.5 | 93272 | 85935 | -0.003934 | -6.95 | 0.004794 | 8.00 | -0.008728 | -9.15 |
| 1,150,1 | 35746 | 36258 | -0.009691 | -5.28 | 0.005113 | 5.81 | -0.009691 | -5.28 |
| 1,200,0 | 238597 | 218038 | -0.002969 | -7.49 | 0.003351 | 7.95 | -0.006320 | -13.26 |
| 1,200,0.5 | 109824 | 99342 | -0.003235 | -6.12 | 0.004052 | 7.17 | -0.007287 | -8.60 |
| 1,200,1 | 47981 | 47096 | -0.004028 | -5.32 | 0.004007 | 5.13 | -0.008036 | -5.42 |

**Table 5:** Test Results for the WMA for 5-minute silver data over the period 2008-2014. N(Buys) and N(Sells) are the number of buy and sell signals. Buy and Sell refer to the average returns from buy and sell signals with their associated z-statistics. Buy-Sell denotes the average return from the moving average strategy along with the z-statistics. \*\*\*, \*\*, \* indicate significance at 1%, 5% and 10%.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| RULE | N(BUYS) | N(SELLS) | BUY | BUY z-stat | SELL | SELL z-stat | BUY-SELL | BUY-SELL z-stat |
| 1,50,0 | 231327 | 225414 | -0.006740 | -16.68 | 0.007027 | 16.98 | -0.013767 | -29.09 |
| 1,50,0.5 | 33634 | 33214 | -0.006292 | -7.04 | 0.007449 | -7.04 | -0.013741 | -6.62 |
| 1,50,1 | 8130 | 9356 | -0.004879 | -2.76 | 0.005041 | 2.99 | -0.009921 | -1.75 |
| 1,100,0 | 233461 | 223274 | -0.004918 | -12.24 | 0.005249 | 12.61 | -0.010166 | -21.45 |
| 1,100,0.5 | 59287 | 56511 | -0.005839 | -8.46 | 0.006784 | 9.46 | -0.012623 | -9.36 |
| 1,100,1 | 18338 | 19441 | -0.012244 | -4.58 | 0.006792 | 5.77 | -0.012244 | -3.98 |
| 1,150,0 | 235573 | 221111 | -0.003725 | -9.33 | 0.004072 | 9.73 | -0.007796 | -16.42 |
| 1,150,0.5 | 78863 | 73795 | -0.004872 | -8.00 | 0.005691 | 8.91 | -0.010562 | -9.74 |
| 1,150,1 | 27985 | 28855 | -0.004838 | -4.97 | 0.006290 | 6.44 | -0.011129 | -5.00 |
| 1,200,0 | 236790 | 219844 | -0.003190 | -8.01 | 0.003537 | 8.42 | -0.006728 | -14.15 |
| 1,200,0.5 | 94526 | 87379 | -0.003913 | -6.95 | 0.005166 | 8.68 | -0.009079 | -9.61 |
| 1,200,1 | 37303 | 37355 | -0.004663 | -5.48 | 0.006304 | 7.28 | -0.010968 | -6.12 |

**Table 7:** Summary results of the parameter sweep on parameters of the three moving average rules. ‘P’ denotes the percentage of positive buy-sell differences and ‘N’ denotes the percentage of negative buy-sell differences. ‘S’ refers to the percentage of significant positive/negative buy-sell differences.

|  |  |  |  |
| --- | --- | --- | --- |
| Rule | P (S) | N (S) | Best Rules |
| Panel A: Gold | | | |
| SMA | 56.42% (20.15%) | 43.56% (21.28%) | 44-332, 44-331, 40-356, 43-325, 42-330 |
| EMA | 56.27% (1.30%) | 43.73% (28.35%) | 49-259, 46-386, 48-263, 47-266, 49-262 |
| WMA | 32.68% (1.91%) | 67.32% (49.96%) | 49-498, 49-487, 49-490, 49-496, 49-497 |
| Panel B: Silver | | | |
| SMA | 36.16% (0.00%) | 61.84% (17.94%) | 45-300, 45-286, 45-301, 45-299, 45-296 |
| EMA | 23.53% (0.00%) | 76.47% (29.45%) | 48-380, 48-381,48-379, 48-378, 49-374 |
| WMA | 9.98% (0.00%) | 90.02% (41.68%) | 49-347, 49-350, 47-348, 49-346, 49-351 |

**Table 8:** The in- and out-of-sample results for the best performing technical trading rules.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  | In-Sample | | Out-of-Sample | |
| Rule | Best Rules | Buy-sell | Buy-Sell z-stat | Buy-sell | Buy-Sell z-stat |
| Panel A: Gold | | | | | |
| SMA | 41-356 | 0.001040 | 2.23 | 0.000581 | 2.27 |
| 41-357 | 0.001037 | 2.23 | 0.000585 | 2.28 |
| 42-359 | 0.001024 | 2.20 | 0.000554 | 2.16 |
| 41-352 | 0.001022 | 2.20 | 0.000609 | 2.38 |
| 42-362 | 0.001019 | 2.19 | 0.000523 | 2.04 |
| EMA | 49-155 | 0.000539 | 1.15 | 0.000204 | 0.80 |
| 48-162 | 0.000502 | 1.08 | 0.000163 | 0.64 |
| 48-157 | 0.000502 | 1.08 | 0.000184 | 0.72 |
| 48-163 | 0.000497 | 1.07 | 0.000175 | 0.68 |
| 49-160 | 0.000496 | 1.06 | 0.000180 | 0.70 |
| WMA | 48-413 | 0.000594 | 1.27 | 0.000444 | 1.73 |
| 46-437 | 0.000593 | 1.27 | 0.000467 | 1.82 |
| 48-443 | 0.000589 | 1.26 | 0.000483 | 1.88 |
| 47-440 | 0.000589 | 1.26 | 0.000431 | 1.68 |
| 49-444 | 0.000588 | 1.26 | 0.000493 | 1.92 |
| Panel B: Silver | | | | | |
| SMA | 27-485 | 0.001540 | 1.82 | -0.000582 | -1.03 |
| 27-498 | 0.001537 | 1.81 | -0.000532 | -0.94 |
| 24-497 | 0.001533 | 1.81 | -0.000633 | -1.11 |
| 27-497 | 0.001528 | 1.80 | -0.000510 | -0.90 |
| 27-496 | 0.001519 | 1.80 | -0.000516 | -0.91 |
| EMA | 47-414 | 0.001719 | 2.03 | -0.000599 | -1.06 |
| 47-415 | 0.001710 | 2.02 | -0.000600 | -1.06 |
| 48-408 | 0.001685 | 1.99 | -0.000625 | -1.10 |
| 48-421 | 0.001675 | 1.97 | -0.000556 | -0.98 |
| 48-420 | 0.001675 | 1.94 | -0.000590 | -1.04 |
| WMA | 47-495 | 0.000867 | 1.03 | -0.000236 | -0.42 |
| 47-494 | 0.000850 | 1.01 | -0.000242 | -0.43 |
| 47-496 | 0.000843 | 1.00 | -0.000258 | -0.45 |
| 47-493 | 0.000839 | 0.99 | -0.000286 | -0.50 |
| 49-456 | 0.000832 | 0.98 | -0.000251 | -0.44 |

|  |  |  |  |
| --- | --- | --- | --- |
| Rule | Best Rules | Buy-sell | Buy-Sell z-stat |
| Panel A: Gold | | | |
| SMA | 34-339 | 0.000752 | 2.93 |
| 34-350 | 0.000749 | 2.92 |
| 34-338 | 0.000746 | 2.91 |
| 34-349 | 0.000744 | 2.90 |
| 30-308 | 0.000743 | 2.90 |
| EMA | 49-260 | 0.000652 | 2.54 |
| 49-259 | 0.000651 | 2.54 |
| 49-261 | 0.000651 | 2.54 |
| 45-386 | 0.000650 | 2.52 |
| 46-286 | 0.000646 | 2.51 |
| WMA | 48-483 | 0.000603 | 2.35 |
| 48-482 | 0.000596 | 2.32 |
| 48-481 | 0.000596 | 2.32 |
| 48-484 | 0.000594 | 2.31 |
| 47-485 | 0.000594 | 2.31 |
| Panel B: Silver | | | |
| SMA | 49-301 | 0.000704 | 1.24 |
| 45-300 | 0.000693 | 1.22 |
| 45-301 | 0.000673 | 1.19 |
| 48-304 | 0.000667 | 1.18 |
| 45-299 | 0.000666 | 1.17 |
| EMA | 49-217 | -0.000298 | -0.52 |
| 48-217 | -0.000298 | -0.53 |
| 48-203 | -0.000299 | -0.53 |
| 49-258 | -0.000306 | -0.54 |
| 49-219 | -0.000308 | -0.54 |
| WMA | 49-349 | 0.000137 | 0.24 |
| 49-350 | 0.000136 | 0.24 |
| 49-351 | 0.000130 | 0.23 |
| 49-344 | 0.000126 | 0.22 |
| 49-347 | 0.000126 | 0.22 |

**Table 9:** The best performing technical trading rules in the out-of-sample period.

**Table 10:** The bootstrapped simulation results for the best five rules over the full sample and the in- and out-of-sample periods.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Full Sample period | | In-Sample | | Out-of-Sample | |
|  | Best Rules | p-value | Best Rules | p-value | Best Rules | p-value |
| Panel A: Gold | | | | | | |
| SMA | 44-332 | 0.00 | 41-356 | 0.01 | 34-339 | 0.00 |
| 44-331 | 0.00 | 41-357 | 0.01 | 34-350 | 0.00 |
| 40-356 | 0.00 | 42-359 | 0.01 | 34-338 | 0.00 |
| 43-325 | 0.00 | 41-352 | 0.02 | 34-349 | 0.00 |
| 42-330 | 0.01 | 42-362 | 0.01 | 30-308 | 0.00 |
| EMA | 49-259 | 0.01 | 49-155 | 0.13 | 49-260 | 0.01 |
| 46-386 | 0.01 | 48-162 | 0.15 | 49-259 | 0.00 |
| 48-263 | 0.01 | 48-157 | 0.14 | 49-261 | 0.01 |
| 47-266 | 0.01 | 48-163 | 0.16 | 45-386 | 0.00 |
| 49-262 | 0.01 | 49-160 | 0.14 | 46-386 | 0.01 |
| WMA | 49-498 | 0.01 | 48-413 | 0.12 | 48-483 | 0.01 |
| 49-487 | 0.02 | 46-437 | 0.09 | 48-482 | 0.01 |
| 49-490 | 0.01 | 48-443 | 0.12 | 48-481 | 0.01 |
| 49-496 | 0.01 | 47-440 | 0.12 | 48-484 | 0.01 |
| 49-497 | 0.01 | 49-444 | 0.10 | 47-485 | 0.01 |
| Panel B: Silver | | | | | | |
| SMA | 45-300 | 0.06 | 27-485 | 0.03 | 49-301 | 0.11 |
| 45-286 | 0.06 | 27-498 | 0.04 | 45-300 | 0.13 |
| 45-301 | 0.06 | 24-497 | 0.04 | 45-301 | 0.11 |
| 45-299 | 0.06 | 27-497 | 0.04 | 48-304 | 0.13 |
| 45-296 | 0.06 | 27-496 | 0.04 | 45-299 | 0.11 |
| EMA | 48-380 | 0.23 | 47-414 | 0.02 | 49-217 | 0.69 |
| 48-381 | 0.21 | 47-415 | 0.02 | 48-217 | 0.72 |
| 48-379 | 0.20 | 48-408 | 0.03 | 48-203 | 0.68 |
| 48-378 | 0.24 | 48-421 | 0.03 | 49-258 | 0.72 |
| 49-374 | 0.22 | 48-420 | 0.03 | 49-219 | 0.70 |
| WMA | 49-347 | 0.25 | 47-495 | 0.14 | 49-349 | 0.41 |
| 49-350 | 0.25 | 47-494 | 0.15 | 49-350 | 0.41 |
| 47-348 | 0.28 | 47-496 | 0.16 | 49-351 | 0.44 |
| 49-346 | 0.25 | 47-493 | 0.16 | 49-344 | 0.40 |
| 49-351 | 0.26 | 49-456 | 0.17 | 49-347 | 0.41 |



**Figure 1**: Time-series graph of the Gold and Silver markets over the full sample period



**Figure 2**: The average z-buy-sell statistics for each short-run and long-run parameter.

1. The Brock et al study investigates the period 1897 to 1986. Some studies however have found that the daily predictive power of these rules diminishes and even disappears in the period following the data used by Brock et al (1992) study. For instance see Lebaron (2000), Schulmeister (2009), Fang et al (2014) and Urquhart et al (2015). [↑](#footnote-ref-1)
2. The estimated daily turnover in the international gold market was 4,000 metric tons in 2011 (Hauptfleisch et al 2015) while silver’s demand keeps on rising. The daily turnover of the gold market exceeds the turnover of all but four currency pairs [↑](#footnote-ref-2)
3. Park and Irwin (2007) provide an excellent overview of the literature. [↑](#footnote-ref-3)
4. Generally a 1% band is used in the literature. [↑](#footnote-ref-4)
5. Fawley and Neely (2012) provide a detailed timeline of QE in Figure 2. [↑](#footnote-ref-5)
6. Note that even when there is a zero band with the rule, there are still a number of neutral signals generated given the low deviation in prices. [↑](#footnote-ref-6)
7. We do acknowledge the fact that there is a timing issue of choosing the parameters and that even if a combination of parameters does generate significant predictability, it is unlikely that investors would have been trading that set of parameters to benefit from any predictability. [↑](#footnote-ref-7)
8. Full results can be obtained upon request. [↑](#footnote-ref-8)
9. Zakamulin (2014) shows that moving average and momentum rules performances contain a considerable data-mining bias and that the actual performance out-of-the-sample is highly overstated. [↑](#footnote-ref-9)