Does technical analysis beat the market? – evidence from high frequency trading in gold and silver.

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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 produce significant payoffs in the gold and silver market using three popular moving average rules. We find that using the standard parameters previously used in the literature, technical trading rules offer are not profitable. However after utilising a universe of parameters, we find a number of parameter combinations offer significant profits in the gold market, but there remains no significant payoff in the silver market. Our results show that parameters that use longer histories are more successful than the traditional parameters chosen in the literature. Intraday technical trading rules can be profitable in the gold market but offer no significant profit in the silver market.

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1. Introduction

The efficient market hypothesis (EMH) is one of the most studied and most influential of all theories in the finance literature. In its weak-form, (stock in initial studies but more generally any asset) prices reflect all available information, such that technical analysis trading rules based on historical price data will not be profitable (Fama 1970). However, trading models based on technical analyses that employ momentum or trend following technology have been found to have significant positive payoffs (Brock et al., 1992 amongst others.))[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. Technical analysis in its varied forms is widely used across all asset classes.

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

Gold and silver are easily traded and have the advantage of being priced in a common currency, and 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 straightforward and follows other work flowing from Brock et al. 1992. Initially, we examine the gold and silver price series using simple, exponential and weighted moving average rules to determine whether these trading rules are profitable. 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 as to 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.

[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).

Nevertheless, any significant payoffs 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 issue we run an in- and out-of-sample test to study whether the most profitable 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 is profitable in spot precious metal markets at high-frequency. While some studies examine the profitability of technical trading in gold and silver daily spot or daily futures markets, we examine the payoffs 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 profitable. 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 profit 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 focused on the profitability of technical trading rules has used daily data[2] (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 profitability 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 gold and silver given increased attention on them 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 great 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 finding led to an explosion of studies scrutinising the results (see for instance Bessembinder and Chan 1998; Sullivan et al 1999; Day and Wang 2002;

[2] Park and Irwin (2007) provide an excellent overview of the literature.

Ready et al 2002) and studying the performance of technical trading rules in other markets (see for instance Hudson et al 1996; Ito 1999; Fifield et al 2005; Metghalchi et al 2012). 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), Schulmeister (2009) argues that 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 before 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. Using two bootstrap methodologies they find 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 rules from 1960 to 2007 and find that when based on daily data, the profitability of technical rules 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 technical strategy beats the buy-and-hold strategy within their sample. Duvinage et al (2013) investigate the predictive power of Japanese candlestick rules at 5-minute intervals on 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, concluding that the predictive power of Japanese candlesticks is too limited for use in active portfolio management.

Recently, 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.

Studies of technical trading rules applied to gold and silver markets have been sparse, with Marshall et al (2008b) studying 7000 rules on 15 major commodity futures, including gold, and 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) claim that investors can make profits in daily commodity spot markets from technical trading rules. In addition, Narayan et al (2014) study momentum-based trading strategies in commodity futures markets and rank the commodities based on their profitability from 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. In general these studies have found that Gold does not appear to amenable to a trading rule. They also use futures data while here we use OTC data.

There is a distinct lack of studies examining the intraday predictability of technical trading rules and no studies examining the intraday performance of spot gold and silver markets. 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, so 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 asset price 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 (calculated over S days, $S < L$). The buy signal is generated when the short-period moving average moves higher than the long-period moving average:

$$\left[\sum_{\lambda=1}^{S} P_{t-(\lambda-1)} \Big/ S\right] > \left[\sum_{\lambda=1}^{L} P_{t-(\lambda-1)} \Big/ L\right] + band \;\Rightarrow Buy\ at\ time\ t \qquad (1)$$

Where P_t is the price at time t and t evolves in 5-minute intervals. Sell signals are generated when the inequality is reversed:

$$\left[\sum_{\lambda=1}^{S} P_{t-(\lambda-1)} \Big/ S\right] < \left[\sum_{\lambda=1}^{L} P_{t-(\lambda-1)} \Big/ L\right] + band \Rightarrow Sell\ at\ time\ t \qquad (2)$$

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[3]. 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 price rises above (below) the moving average, the signal is to buy (sell).

We also study two variations of the SMA. The exponentially-weighted moving average (EMA) rule where more weight is given to recent observations, the weight of each price change decreasing exponentially. The weighting factor in an EMA is based on a smoothing factor generated by the length of the input. The second is the weighted moving average (WMA) rule, it

[3] Generally a 1% band is used in the literature.

is similar to the EMA but with linear weighting, that is, the most recent price get the greatest weight and each price preceding that gets a smaller 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. Although there is debate on the extent to which the OTC market leads the futures market or vice versa (see (Hauptfleisch et al 2015)) the OTC market in precious metals trades significantly more volume than does the futures. 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) in an analysis of foreign exchange data argues that 5-minute intervals are the best compromise, this is the length we have chosen. Gold and silver both trade from Sunday 22.00 to Friday 20.45, with a daily break between 21.00 and 22.00 GMT. Following Hol and Koopman (2002), we define the 5-minute return as:

$$r_{t,d} = \left(In\ P_{t,d} - In\ P_{t,d-1}\right)\times 100 \tag{3}$$

where $r_{t,d}$ 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 which we remove the observations. Following 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. Over this period gold and silver markets have become more popular and liquid, as well as attracting more attention in the finance literature. Table 1 presents the summary statistics of our price data as well as the return series. For the return series, we examine the distributional characteristics using the following statistics: mean, standard deviation, skewness, kurtosis and the Jarque-Bera test for normality. As expected both return series have a near zero mean, 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 consistent with weak-form market efficiency and so should preclude abnormal returns based on trend following trading rules.

We also examine the autocorrelation of the two series using the Ljung-Box (Q-stats) test at lags 6, 12 and 24, along with the estimated autocorrelation at lags of 1 to 5. 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, 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 mean reverting returns following an information shock. Such market movements could provide exploitable market trading (i.e. buy or sell the asset at time interval 2 or 3 after a negative or positive information shock 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[4]. 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) than zero. The buy-sell differences are all negative, the vast majority are statistically significant indicating no predictive power in the 5-minute gold data for the SMA and EMA rules listed. 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, the vast majority being 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 the buy-sell differences are negative and statistically significant indicating no predictive power of the SMA and EMA rules 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 for the WMA in the 5-minute silver market.

Our initial results on high-frequency moving average trading rules show that there is no predictive power from these rules, with the parameters presented, in either market. This finding is consistent with the weak form of market efficiency.

5.2. Parameter Sweep

In the previous section we found that popular parametrisations of moving average rules do not have predictive power when applied to the high-frequency prices of gold and silver. However we predetermined the parameters of the technical trading rules based on their popularity in the literature. These parametrisations may not be optimal trading rules, so we run a parameter sweep on our trading rules so ensure that the results found in the previous section are robust[5]. This involves running 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 a total 66297 different moving average rules.

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[4] 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.

[5] We acknowledge the fact that there is a timing issue in 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.

The summary of results[6] is reported in Table 6 where we show that for gold, 56.42%, 56.27% and 32.68% of the SMA, EMA and WMA rules studied generate positive profits. However 20.15%, 1.30% and 1.91% of these rules generate positive significant profit, indicating that the SMA is the most successful of the moving average rules, with the EMA and WMA offering very little significant profitability. Similar to the gold results, the silver results show that some of the parameter combinations for the three moving average rules generate positive profit. However none of the 66297 moving average rules studied generate significant profitability, suggesting that the intraday silver market is efficient with respect to these technical trading rules.

Table 6 also reports the best five parameterisations 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 and 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 lengths should be longer than those traditionally used in studies that use daily data. This result is confirmed for silver the most profitable moving average rule parameters are 45-300, 48-380 and 49-347 for the SMA, EMA and WMA respectively.

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

5.3. In- and out-of-sample testing

We have shown that the standard parameters used in technical trading studies in the literature fail to generate any significant profits, however using a parameter sweep we show that some combinations of short-run and long-run parameters give rise to significant profits. Any significant profitability from the parameter sweep may be due to data-mining. If this is the case there would be no rationale for an investor to select those specific parameters in that time period[7]. To overcome this problem 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 in sample we select the five rules with the greatest buy-sell z-statistic. We use the Bai and Perron (2003) structural break test to determine the 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 the global maxima observed for each series in Figure 1.

Table 7 reports the parameters of the five best trading rules found in the in-sample period and the performance of those rules in the out-of-sample period. The gold results reported in Panel A

[6] Full results can be obtained upon request.

[7] 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.

show that the SMA is again the most successful rule in the in-sample period, with the five best performing rules generating significant profits. We find that the most successful rules in-sample also generate positive profits 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 profitability actually increases out-of-sample, although none move from insignificant to significant. Panel B reports the silver results, it shows that the best performing SMA, EMA and WMA rules in-sample are not profitable out-of-sample. Only 4 of the best 15 rules from the SMA, EMA and WMA rules offer any significant profit in the in-sample period. However these rules in the out-of-sample period offer negative payoffs indicating that investors would have not have gained any positive returns from following the best performing in-sample trading rules in the out-of-sample period. In summary, Table 7 shows that the best SMA, EMA and WMA rules in the in-sample periods for gold do offer some profits in the out-of-sample period, however the best performing rules for silver in the in-sample period offer no payoff in the out-of-sample period.

For completeness we compute a parameter sweep in the out-of-sample period for gold and silver and report the best performing rule for the SMA, EMA and WMA, which is reported in Table 8. All the five best SMA, EMA and WMA rules for gold offer significant profits indicating that technical trading rules in the out-of-sample period do offer value to investors. Investors may have no rationale for choosing the successful parameters as they are different to the best performing rules in the in-sample period. Panel B reports the silver results showing that the five best SMA and WMA rules offer positive but insignificant payoffs, while the EMA rules offer no profit at all. This is consistent with our earlier results that technical trading rules offer very little profitability in the silver market. Again, none of these rules are the best performers' in-sample, so investors would have no rationale to select these parameters.

5.4. Bootstrap Analysis

Data snooping is a concern when studying the profitability of any technical trading rule. To examine the robustness of our results and to judge the statistically significance of our results, we employ the bootstrap approach suggested by Okunev and White (2003) that was used by Narayan et al (2014; 2015). This bootstrap method randomly selects a sample of prices, with replacement, for each of gold and silver. As a result a new data set is generated which retains the characteristics of the original data set. The bootstrap p-values are the percentage of simulated mean returns that are greater than the actual mean returns calculated using 1000 replications. 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 bootstrapped results are reported in Table 9. They are consistent with our previous analysis in that rules that were found to generate significant profits also generate significant payoffs when bootstrapped. The full sample gold results for all three rules as well as the in-sample SMA rule are statistically significant, indicating the significant profitability of these rules. The best rules in the out-of-sample period are statistically significant, consistent with our previous analysis. Panel B reports the silver results, the results support our previous finding that only the best SMA and EMA rules in the in-sample generate significant profit and all other rules in the full sample and out-of-sample periods fail to generate any significant payoff.

6. Summary and Conclusions

This paper studies the profitability of intraday technical analysis in the gold and silver spot markets. Prior work in this area has mostly focussed on daily data, 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 found in the literature. We also conduct a parameter sweep where we examine all possible combinations of parameters for these technical trading rules, 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-sample can be used to generate significant profits in the out-of-sample period.

The initial results show that the SMA, WMA and EMA trading rules generate significant negative payoffs using the parameters common in the literature in the high-frequency gold and silver markets. This suggests that there is no significant profit to be gained from technical trading in the gold and silver markets. However, our parameter sweep results show that there are a number of parameter combinations that generate significant profit in the gold market, but none in the silver market. Further, the best performing rules have different parameters to those used the existing literature. We show that longer run averages should be used by investors on intraday data and that investors 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 profits 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 payoffs in the out-of-sample period. Finally we perform a bootstrap analysis, which confirms our previous findings.

Our results demonstrate that intraday technical trading rules can be profitable in the gold market but intraday investors need to select parameters which are appropriate to the frequency of the data. These parameters will be different to those used by investors who trade on daily data. We also show that silver offers no significant profits, suggesting that the silver market is weak form efficient.

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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
Panel A: Prices		
N	500039	456835
Mean	1301.75	23.2367
SD	297.19	8.1286
Skew	-0.08	0.4896
Kurt	-1.13	2.3491
JB	26907***	26314.92***
Max	1919.69	49.46
Min	684.40	8.50
Panel B: Returns		
N	500038	456834
Mean	8.01×10^{-5}	5.35×10^{-5}
SD	0.000833	0.001596
Skew	-0.49	-1.47
Kurt	88.24***	107.73***
JB	1.51×10^{8}	2.09×10^{8}
$\rho(1)$	-0.062***	-0.092***
$\rho(2)$	-0.010***	-0.004***
$\rho(3)$	-0.008***	0.010***
$\rho(4)$	-0.001	0.003***
$\rho(5)$	-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 6: 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 7: 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					
	41-356	0.001040	2.23	0.000581	2.27
	41-357	0.001037	2.23	0.000585	2.28
SMA	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
	49-155	0.000539	1.15	0.000204	0.80
	48-162	0.000502	1.08	0.000163	0.64
EMA	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
	48-413	0.000594	1.27	0.000444	1.73
	46-437	0.000593	1.27	0.000467	1.82
WMA	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					
	27-485	0.001540	1.82	-0.000582	-1.03
	27-498	0.001537	1.81	-0.000532	-0.94
SMA	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
	47-414	0.001719	2.03	-0.000599	-1.06
	47-415	0.001710	2.02	-0.000600	-1.06
EMA	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
	47-495	0.000867	1.03	-0.000236	-0.42
	47-494	0.000850	1.01	-0.000242	-0.43
WMA	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

Table 8: The best performing technical trading rules in the out-of-sample period.

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

Table 9: 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

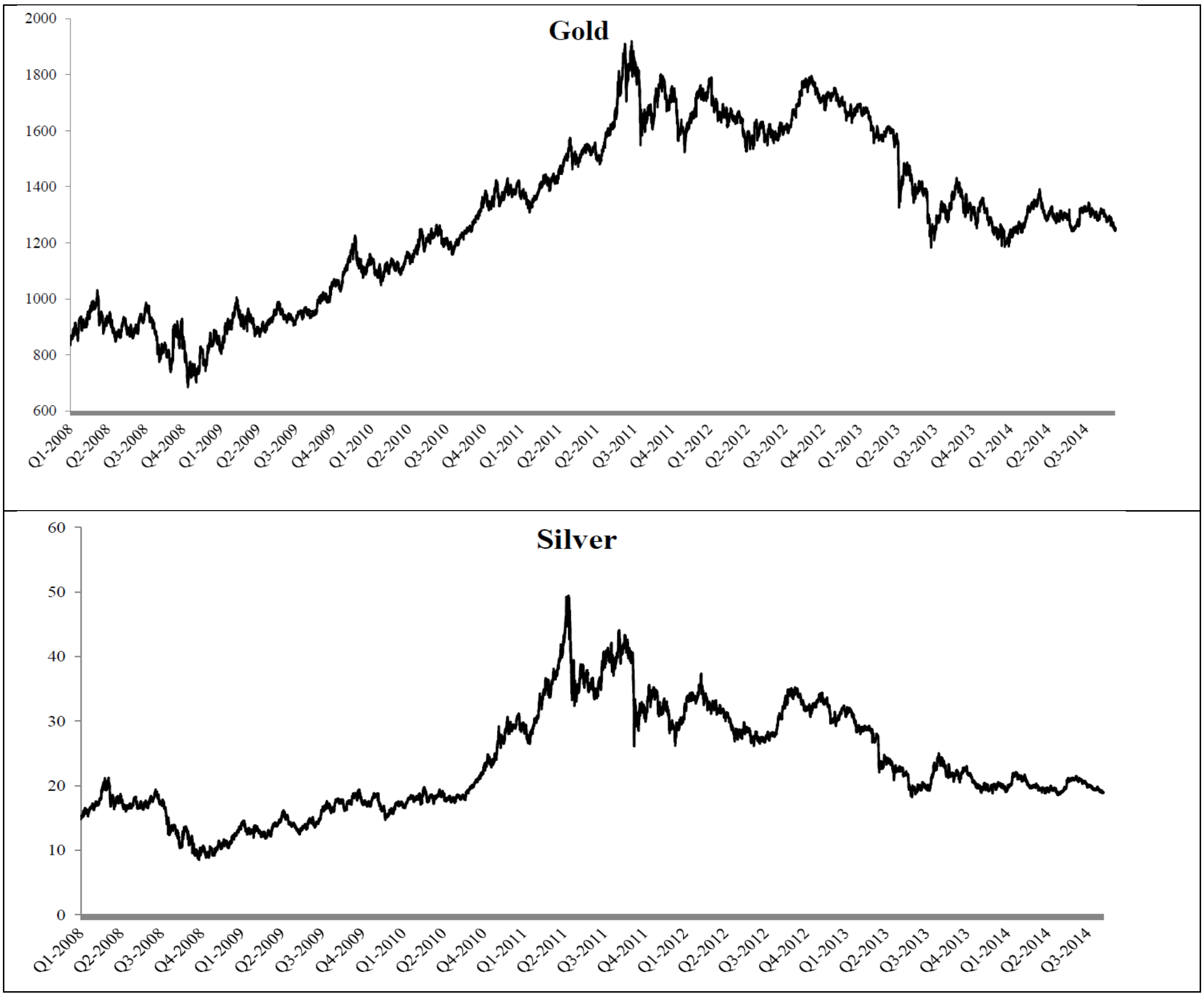

Figure 2: The average z-buy-sell statistics for each short-run and long-run parameter of the various moving average rules.