Can Risk Premium Explain Technical Trading Profits? A Study of the UK Markets

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ABSTRACT

Over the past two decades studies of the efficacy of trading rules have increasingly found returns to be predictable and presence of statistically significant abnormal returns out-of-sample. Despite the fact that technical trading can have relatively less volatile returns due to being in and out of the market, some previous studies have explained their abnormal returns as compensation for risk premium. These studies have shown that periods of higher returns are associated with periods of greater volatility and that any profits remaining after adjusting for risk are statistically insignificant. In this article we use rolling windows for estimating and calculating relevant risk for evaluating technical trading profits. While noting the difficulty of modelling risk, this article concludes that there is no sufficient evidence to support the idea that markets are not efficient on a risk adjusted basis.

Introduction

Measuring risk takes centre stage in the evaluation of the efficiency of financial markets given its central role in investment performance evaluation. Since the evaluation of weak form efficiency via technical analysis is in fact an evaluation of the performance of trading models, the argument of risk concerns becomes even more important. In the past two decades an increasing number of studies have found excess profits from technical analysis to be significant out of sample.[1] Some of these studies have concluded that such abnormal excess profits are a compensation for bearing time varying risk premium.

Neely (2001) observes that because technical trading strategies spend some time out of the market, they should therefore have less volatile returns than the buy and hold rule. Despite this rather compelling argument, most of the literature position technical trading strategy as generally more riskier than the buy and hold strategy. This view in the literature is supported by the empirical evidence where estimates of risk from buy and hold strategy have been found to be less than the estimated risk from trading rule strategies. Second, despite the numerous documentations in literature that discuss the heteroskesdastic nature of financial asset distributions, the standard deviation as a measure of risk is still being captured as a stationery statistic throughout the entire investment period.

Campbell et. al. (1997, p.481) argued that "it is both logically inconsistent and statistically inefficient to use volatility measures that are based on the assumption of constant volatility over some period when the resulting series moves through

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[1] This is particularly for studies that used sample periods that covered the years of the late 1980s to the mid 1990s.

time." Because the standard deviation is calculated as an average dispersion of all the observations in the sample, the implied perception in its traditional calculation is that it is stationery. This perception allows its calculation to ignore the chronological order of events (reflected in contiguous price movements) which could be important if it is used to estimate risk of strategies that are time varying nature.

Risk estimates should consider the periods that actually matter to the investor.[2] The periods that matters are the short or long periods that traders switch assets between long and short positions by following trading signals. Ideally, risk estimates should be able to chronologically track down the relative risks for technical trading and buy and hold strategies during these periods. Unfortunately the standard deviation does not consider the chronological order of occurrences of price movements along the time line. The standard deviation is calculated using values of observations regardless of the chronological order in which these values occurred. This can be a source of bias if this statistic and other associated risk estimates like the Sharpe ratio are used in evaluating the efficacy trading rules strategies.

The work of Dacoragna et. al.(2001) points that the Sharpe ratio does not take account of clustering of profits and losses and its instability as the variance of an investment approaches zero. They propose performance measures which observe returns over different time intervals.

[2] Some aspects of stock trading make technical trading an obvious risky strategy compared to the buy and hold strategy. The risk of shorting, the risk of liquidity and the 'bad signal' risk. These can be described as risks associated with technical trading than buy and holding. The buy and hold rule does not take these risks. These are what should concern the technical trader for the risk of her strategy relative to the buy and hold alternative.

Dacorogna et. al. (2001) also observe that the Sharpe ratio treats the variability of returns and variability of losses in the same way despite the fact that the variability of profits is not an issue of concern to a risk aversive investor.

This article extends the literature on the relationship between technical analysis and risk adjustment by investigating whether technical trading rules are useful on a risk-adjustment basis in equity markets by adapting the technique used by Dacorogna et. al (2001) to the UK market. The article uses a multi-horizon framework to capture the chronological order of price movements where time intervals (windows) are conceived to open and close on the occurrence of trading signals and not fixed as in Dacorogna et. al.'s (2001) case.

In this article risk estimates are explored in the context of the investment strategies in the stock markets. Sixty four stocks from the London Stock Exchange (LSE) are examined. The sample runs from 1st Jan, 1990 to 31st December, 2004. The rules fail to significantly and consistently outperform the buy and hold strategy even after using the rolling standard deviation as a measure of risk. Thus this article extends results in previous studies which found that return predictability and apparent trading rule profits are consistent with market efficiency.

The rest of this article is organised as follows. In the next section, the objectives and significance of this article are described. In section three these is a summary of previous related works in this area, summarizing statistics that have been attempted, their contributions and pitfalls. In section four the conceptual framework for this article is developed. Section 5 provides the methodology including data and testable hypotheses. The results are presented in section 6 and section 7 concludes the article.

Literature Review

The seriousness of appropriately adjusting for risk has been highlighted by several researchers (Jensen, 1967; Kho, 1996; Ready; 2002, Allen and Karjalainen, 1999; and Neely, 2001; 2003). Recent studies on technical analysis that have explained significant excess profits out of sample as a compensation for risk premium includes Cheng and Wong (1997), Lee et. Al. (2001), Kho (1996), Levich and Thomas (1993), and Sweeney (1988).

The problem that documented measures of risk used to evaluate the efficacy of technical trading rules do not reflect the real risk concerns of a technical trader were first addressed by Dacoragna, et al (2001). The Reff statistic of Dacoragna, et. Al. (2001) captures changes in investors utility and appetite for risk across the sample period on the assumption that investor's risk attitude can be altered by certain events. Specifically the Reff recognizes that the consequential impact of trading losses can be higher to a moderate than to a wealthy investor. Hence the Reff assigns high risk aversion in the windows with negative returns and a low one in the windows with profits. The Xeff on the other hand measures the utility that the trading strategy gives an excess return over a weighted average of return horizons.

The Conceptual Framework

The distribution of returns seldom represents appropriately the actual chronological order of price movements. Even in the case where there are large drawdowns these are nevertheless represented by price movements which evolve in time to a minimum low. This is especially serious when using quantities to assess the efficacy of weak form efficiency of the Efficiency Market Hypothesis (EMH) because the risk inferred by the statistics could be biased.

The intervals of time in which a trader takes a position are governed by the generation of alternating buy and sell signals. Thus each period of time between two contiguous buy and sell signals can be considered to have different volatility estimates. The intuition available is that each of these fairly short horizons contain its own return variability, a variability that is more associated with the chronological order of price movements within the window itself.

In order to capture the chronological order of risk attracting events the rolling windows technique is used to capture periods that represent the order of price movements. A window, ?ti, is defined as a period of time from a signal is issued by a trading rule up to the next signal, for i = 1,2, ... n-1, where n is the total number of trades executed throughout the investment period.

$$X_{eff} = \frac{252.100}{T}\left(\sum_{t=1}^{T} r_t - \frac{n}{2}\ln\left(\frac{1+c}{1-c}\right)\right) - \frac{\sum_{i-1}^{n} \tilde{w}_i \sigma_i^2 (1year/\Delta t_i)}{\sum_{i=1}^{n} \tilde{w}_i} \quad (1)$$

The same weighting scheme used by Dacorogna et. al. (2001) is used in this article except that the length of the window, ?t, in our case are given by length of windows as determined by the occurrence of the buy and sell signals.This innovation is intended to make the risk estimate more realistic by affecting the widely recognised fact that equals in upward and downward deviations do not inflict the investor with equal risk.

A different length of time is also used to proxy the maximum value the sequence of weights can take. While accepting the arguments used by Dacorogna et. al. (2001) for their choice of 90 days, we consider more appropriate to use the days where the memory effect is still strong. Thus, the weight is calculated as;

$$\tilde{w}_i = \frac{1}{2 + \left(\ln\left(\frac{\Delta t_i}{d}\right)\right)^2} \quad (2)$$

where d is the number of days the autocorrelation effect is still significant. The other variables are as defined before.

By executing a 10 days fixed moving average rule, our shortest window has at least 10 observations. This is still too short for high precision standard deviation. The number of observation points is increased in each window by following Muller et. al. (1993) who advices the use of overlapping intervals in computing the standard deviation. Standard deviations from each window are then annualised before calculating the average for the entire sample.

Methodology

The sample runs for the period from 1st January 1990 to 31st December 2004. The sample comprises of 64 stocks from the London Stock Exchange where all data is obtained from the Datastream database (See table 1 in the Appendix). We implement a simple recursive trading strategy is implemented to simulate real-time speculation. Specifically, the investor is assumed to trade each day using the MA rule that is considered "best" using data up to the previous day. Following Sullivan et. al. (1999), the best MA rule is defined as the rule that has the highest cumulative returns over the past ninety days.[3] These rolling ninety days means that the evaluation is done every day. Ten trading rules are used that were originally used by Brock et. al. (1992).

Empirical Results

Summary Statistics

Table 2 presents a summary of statistics for the average of the 64 individual stocks from a sample of stocks from the FTSE 100 for the period from January 1990 to December 2004. The summary contains the distribution characteristics mean standard deviation,skewness and kurtosis. Return is defined as the natural logarithm of value relatives, which is similar to the arithmetic return for small values. The statistics indicates that there is dependency in the return generating process. The stock prices do not give indication of random walk symptoms.

The Rolling Standard Deviation vs The Traditional Standard Deviation

The test of the difference between the standard deviation of returns from trading rules calculated using the traditional entire sample approach and the standard deviation determined using a non-overlapping rolling approach was analysed via Table 3. Only 22.5% of results indicate there is significant difference while 77.5% indicate thatthere is no difference. Of the 22.5% only 11.72% indicate that the standard deviation of returns from trading rules based on the rolling approach is significantly less than standard

[3] The ninety days is derived as an average of the long moving averages for all the 26 trading rules available to the trader

deviation based on the traditional entire sample approach. The remaining 10.78% holds that the traditional approach gives standard deviation which is significantly less than the rolling approach. These results, however, are not sufficient to reject the null of equality of the two estimates of risk.

Does Technical Analysis Provide more Stable Portfolios?

It is also useful to test whether a technically managed portfolio is more profitable than the buy and hold portfolio after risk adjustment because the volatility of returns from the former are calmed by the switching to asset types of lower volatility. The general position of literature, as mention earlier, is that actively managed portfolios are more riskier than passively managed portfolios. We, therefore, compare a passively managed buy and hold portfolio with an actively managed portfolio both adjusted by their respective rolling standard deviations.

With the exception of only three trading rules, the average returns from the trading rules exceed those from the buy and hold strategy in all models tested. This is consistent with most previous studies including Hudson et. al. (1996) and Taylor (2000). It was noted by Hudson et. al. (1996), that reporting on averages can distort the true picture when examining the performance of individual stocks or individual trading rules. Results indicate that only 76 counts out of 460 models have trading rules exceeding the buy and hold strategy at 5 % level of significant. This is only about 16% of superior performance for trading rules. It is a weak outcome for the trading rules even when the standard deviation is calculated using the rolling approach.

Effects in Evaluating Profitability and Market Efficiency

Table 4 gives results of test of predictability, which also implies the information value of technical trading rules. The test is used to obtain evidence on the efficiency of the rolling approach standard deviation in testing whether conditioning on information contained in past prices by using trading rules is useful. This is done by comparing the returns from the Buy days against the returns from Sell days. The test statistic, t, is calculated using the formula;

$$\frac{\bar{r}_b - \bar{r}_s}{\left(\frac{s_b^{\,2}}{n_b} + \frac{s_s^{\,2}}{n_2}\right)^{0.5}} \text{ -----------(3)}$$

where $\bar{r}_b$ and $\bar{r}_s$ are the average returns from buy and sell days respectively. $s_b^{\,2}$ and $s_s^{\,2}$ are the variances of returns from Buy and Sell days respectively, while n_b and n_s are the number days in long and short positions respectively.

The results indicate that the stocks were in long positions for more days (an average of 1596 days) than they were in short positions (average of 1518 days). The difference in the average returns from Buy days and the average returns from Sell days can give evidence about when the two returns are not equal (Taylor, 2000). Trading rules can uncover evidence of predictability of the price process if expected returns depend on Buy/Sell information. The average Buy returns are positive but some Sell returns are negative and overall the average sell returns (5.75% annually) are less than the Buy returns (25.5% annualized). This unadjusted result implies the presence of information in past prices. These results are consistent with Taylor (2000) who also found the past prices of FTSE 100 stocks to have information before risk adjustments are considered. To evaluate market efficiency, the value of this information has to be analysed in the presence of transaction cost and risk. Taylor (2000) observes that:

> *Significant differences between average returns on Buy days and Sell days are only evidence against market efficiency if transaction costs are sufficiently low and special assumptions can be made about risk. A standard assumption made here and in related literature, e.g. Sweeney (1986), is that the risk from holding stock is the same on Buy days as on Sell days. There is no escaping the possibility that there is a time varying risk premium that the trading rules track in such a way that Buy days have a higher average risk premium than Sell days Taylor (2000) pp. 57-58.*

Results on the Buy/Sell risk differences in table 5 show that the returns from Buy days are less volatile (average of 1.593 % per day) than the returns from Sell days (average of 1.673 % per day). The Buy/Sell return series that we have created by concatenating all daily Buy returns into a Buy series, and the same for Sell days, show that out of the 10 trading rules tested the average standard deviation of Buy returns from only 2 trading rules [(1, 150, 0) and (1, 5, 0)] are found larger than those from Sell returns. At the same time the Buy average returns exceed the Sell average return significantly.

Of the 640 models tested, 292 reject the null of no difference between the two, giving evidence that Buy days have larger returns than Sell days. This is against only 40 models which give evidence of returns from Sell days significantly exceeding those from Buy days. This contradicts the implicit assumption of equality of the volatility of the returns from Buy days and those from Sell days in previous studies. These results also give evidence against Taylor's (2000) proposition above that there is a time varying risk premium that the trading rules track in a such a way that Buy days have a higher average risk premium than Sell days.

Risk Adjustment Using the Xeff statistic

Table 5 reports about testing excess profits from trading rules after adjusting using a risk quantity. "Xeff" is the Dacarogna et. al.'s (2001) test statistic for risk adjusted trading rule returns. It is calculated by considering and quantifying the risk via a constant risk aversion factor. A positive Xeff implies that there still remains some profits from trading rules even after deducting transaction costs and risk. Results show that only one rule (5, 150, 0) give an average positive Xeff. But even this positive Xeff is not significant at the 5% level. The rest of the returns are negative.

Conclusions

On the overall, the results indicate that the standard deviation for trading rules returns computed using the rolling approach is lower than when the statistic is calculated using traditional entire sample approach. The rolling approach, therefore, captures the stability in the portfolio returns that is a direct consequence of using a dynamic strategy. When these lower standard deviations are applied to the returns from technical trading rules we are able to conclude that the way the standard deviation is computed can affect the analysis of trading rules performance in terms of the Sharpe ratio.

Our second conclusion regards the comparison of trading rules performance and the buy and hold strategy when the rolling standard deviation is applied in adjusting for risk. Despite the above conclusion that the rolling approach standard deviation is less than the traditional entire sample standard deviation, this approach, however, does not give strong indications that trading rules are more profitable than the buy and hold strategy.

Regarding the test statistic Xeff, consistent with Neely (2001) we find that the use of Xeff does not give sufficient evidence to rationalize apparent profits trading rules. All the results from 10 trading rules averages except one, give a negative Xeff.

On the difference between performances of trading rules during Buy days against Sell days, our findings give strong evidence supporting the idea that more profits can be obtained from conditioning from past prices. The rolling standard deviation was able to capture the order of price movements. However when the overall returns from trading rules is compared with the returns from the Buy and Hold strategy, the Buy and Hold strategy is more superior.

Therefore we can not conclude categorically that risk from active trading is lower than from buy and hold strategy. Nevertheless, we are able to conclude that the use of rolling windows in estimating risk results in risk figures that are lower than risks estimated from traditional standard deviations. A more general conclusion out of the above conclusions is that there is no enough evidence to reject the null of the market is efficient for the FTSE 100 segment of the London Stock Exchange.

In this article we have attempted to track the chronological movement of prices in order to model appropriately the risk that is relevant for technical trading. We have also quantified the risk using a technique suggested by Dacorogna et. al. (2001). While this study has dealt with the aspect of profit or loss clusters, it can still be advanced by considering the fact that volatility of losses gives higher risk to an investor than the volatility of profits. The literature on Lower Partial Moments (LPM) provide excellent connection between risk and performance of investment strategies.

Appendix

Table 1: *List of stocks of the 66 FTSE 100 of the London Stock Exchange for the period January 1990 to December 2004 included in the sample*

1	ABBEY NATIONAL	33	JOHNSON MATTHEY
2	ALLIED DOMECQ	34	KINGFISHER
3	AMERSHAM	35	LAND SECURITIES
4	AMVESCAP	36	LEGAL & GENERAL
5	ASSD.BRIT.FOODS	37	MARKS & SPENCER GROUP
6	AVIVA	38	PEARSON
7	BAA	39	PROVIDENT FINL.
8	BAE SYSTEMS	40	PRUDENTIAL
9	BARCLAYS	41	RECKITT BENCKISER
10	BG GROUP	42	REED ELSEVIER
11	BOC GROUP	43	RENTOKIL INITIAL
12	BOOTS GROUP	44	REUTERS GP
13	BP	45	REXAM
14	BRIT.AMERICAN TOBACCO	46	RIO TINTO
15	BRITISH LAND	47	ROLLS-ROYCE GROUP
16	BT GROUP	48	RYL.BK.OF SCTL
17	BUNZL	49	SAFEWAY (UK)DEAD -
18	CABLE & WIRELESS	50	SAGE GROUP
19	CADBURY SCHWEPPES	51	SAINSBURY (J)
20	DAILY MAIL 'A'	52	SCHRODERS
21	DIAGEO	53	SCHRODERS NV
22	DIXONS GP.	54	SCOT.& NEWCASTLE
23	EMAP	55	SHELL TRANSPORT & TRDG.
24	EXEL	56	SMITH & NEPHEW
25	FOREIGN & COLONIAL	57	SMITHS GROUP
26	GKN	58	STD.CHARTERED
27	GLAXOSMITHKLINE	59	TESCO
28	ITV	60	TOMKINS
29	GUS	61	UNILEVER (UK)
30	HANSON	62	VODAFONE GROUP
31	HILTON GROUP	63	WHITBREAD
32	IMP.CHM.INDS.	64	WPP GROUP

Table 2: *Summary statistic for the stock of the 64 FTSE 100 of the London Stock Exchange for the period January 1990 to December 2004*

Statistic	Mean	S.D.	Kurt	Skew	ρ(1)	ρ(2)	ρ(3)	ρ(4)	ρ(5)
Average for all stocks	0.07527	0.09512	31.76311	0.29265	0.16953*	0.04145	0.02885*	0.02375	0.01603

Note:

Formulas for skewness and kurtosis are $1/n\sum_{i-1}^{n}(x_i - \bar{x})^3 / s^3$, and $1/n\sum_{i-1}^{n}(x_i - \bar{x})^4 / s^4$, respectively. ρ_i is the estimated average for autocorrelation individual stocks at lag i for each individual stock series. Numbers marked with (*) are significant at the 5%.

Table 3: *Comparative analysis of traditional and the rolling approaches to calculating risk from technical trading rules for the stocks of the FTSE 100 of the London Stock Exchange for the period January 1990 to December 2004.*

"rule" is the trading rule applied, while ?tr and ?rol are the annualized standard deviations of returns from technical trading calculated using the traditional method and rolling approach respectively. Columns 4 and 5 contain counts of values t from 64 stocks to which each rule was applied that rejects the null of no difference between the two standard deviations.

rule	σtr %	σro %	t > 1.96	t < 1.96	Rule Return %	Sharpe (σtr)	Sharpe (σrol)
1,150,0	19.290	16.444	3	4	25.560	1.325	1.554
1,50,0	22.927	19.448	6	0	25.296	1.103	1.301
1,200,0	22.452	19.764	14	0	17.784	0.792	0.900
5,150,0	23.085	19.290	8	23	26.352	1.142	1.366
1,50,0.01	28.777	29.884	1	10	20.712	0.720	0.693
1,20,0	32.730	29.251	7	4	15.912	0.486	0.544
1,10,0	24.508	24.191	16	9	30.600	1.249	1.265
1,150,0.01	16.444	12.965	8	3	29.784	1.811	2.297
1,5,0	18.974	14.863	9	6	15.552	0.820	1.046
1,15,0	19.764	13.282	13	7	6.744	0.341	0.508

Table 4 *Analysis of the time varying trading rule performance for the stocks of the FTSE 100 of the London Stock Exchange for the period January 1990 to December 2004.*

rule	# trades (no. of buy signals)	Buy -Return	Buy-TRσrol	Sharpe (Buy-TR)	# trades (no. of sell signals)	Sell-Return	Sell-TRσrol	Sharpe (Sell-TR)	Buy-sell	t > 1.96	t < 1.96
1,150,0	1804	0.074	1.680	0.044	1202	0.009	1.660	0.005	0.065	33	0
1,50,0	1830	0.084	1.530	0.055	1292	0.069	1.550	0.044	0.015	28	6
1,200,0	636	0.147	1.250	0.118	2382	0.055	1.420	0.039	0.092	29	0
5,150,0	1572	0.158	1.040	0.152	1713	0.003	1.220	0.002	0.155	43	8
1,50,0.01	1830	0.101	1.910	0.053	1282	0.024	1.950	0.012	0.077	27	5
1,20,0	2304	0.109	1.480	0.074	792	0.002	1.520	0.001	0.107	21	4
1,10,0	972	0.107	1.790	0.060	2162	-0.032	1.890	-0.017	0.139	27	0
1,150,0.01	1904	0.078	1.220	0.064	1202	0.035	1.460	0.024	0.043	24	6
1,5,0	1344	0.101	1.890	0.053	1802	0.015	1.820	0.008	0.086	39	8
1,15,0	1764	0.065	2.140	0.031	1352	0.052	2.240	0.023	0.014	21	3
Average	1596	0.102	1.593	0.070	1518	0.023	1.673	0.014	0.079	292	40

"rule" is the trading rule applied. "# trades (no. of buy days)" is the number of days in long position. "Buy-Return" is the average daily return per trading rule across the 64 stocks in the sample obtained from taking long positions throughout the sample period. "Buy-TR?rol" is the standard deviation of returns from long positions. "Sharpe (Buy-TR)" is the Sharpe ratio of returns from long positions adjusted using the standard deviation of returns from long positions. "# trades (no. of sell days)" is the number of days in short positions. "sell-Return" is the average daily return per trading rule across the 64 stocks in the sample n obtained from taking short positions throughout the sample period. "Short-TR?rol" is the standard deviation of returns from short positions. "Sharpe (Sell-TR)" is the Sharpe ratio of returns from short positions adjusted with the respective standard deviation of returns from short positions. "buy-sell" is the difference between return from buy and return from sell days for each strategy. Columns 11 and 12 contain counts of values of t from 64 stocks to which each rule was applied that rejects the null of no difference between the buy return and sell returns.

Table 5 *Results of testing excess profits from trading rules after adjusting for risk estimates for the stocks of the FTSE 100 of the London Stock Exchange for the period January 1990 to December 2004.*

Rule	No. of trades	Rule Return (%)	BH Return (%)	Excess Trading rule return	Transaction costs	Xeff	$t > 1.96$
1	2	3	4	5 (3 – 4)	6 (2 x 0.525%)	7 (5 – 6)	8
1,150,0	15	25.56	18.458	7.102	7.84	-0.74	0
1,50,0	21	25.296	15.124	10.172	10.85	-0.68	0
1,200,0	1	17.784	17.415	0.369	0.45	-0.09	0
5,150,0	18	26.352	16.358	9.994	9.37	0.62	0
1,50,0.01	5	20.712	18.163	2.549	2.61	-0.07	0
1,20,0	1	15.912	16.256	-0.344	0.29	-0.64	0
1,10,0	31	30.6	15.345	15.255	16.08	-0.83	0
1,150,0.01	31	29.784	15.483	14.301	16.35	-2.05	0
1,5,0	4	15.552	14.364	1.188	2.02	-0.84	0
1,15,0	7	6.744	15.134	-8.39	3.80	-12.19	0

"rule" is the trading rule applied. "Rule Return" and "BH Return" are the returns from the trading rule and the buy and hold strategy respectively. "Excess Trading rule return" is the average return obtained from dynamic trading throughout the sample period. "Xeff " is the Dacarogna et. al.'s (2001) test statistic for risk adjusted trading rule returns. Column 8 contains counts of values z from 64 stocks to which each rule was applied that rejects the null of no positive Xeff statistic.

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