The Benefits of Combining Seasonal Anomalies and Technical Trading Rules

Bartosz Gebka[a,*], Robert S. Hudson[b], Christina V. Atanasova[c]

[a] Newcastle University Business School, Newcastle University, UK
[b] Hull University Business School, University of Hull, UK
[c] School of Business Administration, Simon Fraser University, Canada

Abstract: Although many seasonal anomalies and technical trading rules have been shown to have predictive ability, investigations have focused only on them operating individually. We study the benefits of trading based on combinations of three of the best known effects: the moving average rule, the turn of the month effect, and the Halloween effect. We show that the rules can be combined effectively, giving significant levels of returns predictability with low risk and offering the possibility of profitable trading. This new investment approach is especially beneficial for a typical individual investor, who faces high transaction costs and is poorly diversified.

Keywords: Technical Trading, Calendar Anomalies, Stock Market Predictability, Market Efficiency

JEL Classification: G11, G12, G14

* Corresponding author: Newcastle University Business School, 5 Barrack Road, Newcastle upon Tyne, NE1 4SE, UK, Tel.; ++44 191 20 81578, Email: b.t.gebka@ncl.ac.uk.

I. Introduction

Despite the general presumption in the finance literature in favor of the unpredictability of returns, there are some areas where predictability is well established. The effectiveness of technical trading rules has been documented in numerous studies, as surveyed by Park and Irwin (2007). Additionally, a large number of investigations confirm the presence of seasonal anomalies in many stock markets: Dzhabarov and Ziemba (2010) outline much of the relevant work in this area and show that many of the anomalies still exist.

In this article, we depart from previous studies that have considered the rules and anomalies on an individual basis and examine the effect of combining them. The types of rules and anomalies (henceforth, for convenience, we will use the term 'rule' for both rules and anomalies) under consideration divide time periods into sub-periods when it is advantageous to be in the market and sub-periods when it is advantageous not to be in the market. When combining rules to obtain a trade signal, there are two fundamental issues to consider: i) the extent to which the different rules would select the same days to be in the market, and ii) the properties of market returns on a particular day conditional on a number of rules indicating that it is advantageous to be in the market on that day. These two aspects, the timing and the conditionality of market returns, generate a wide range of possible combinations of rules. Many of them would not otherwise be apparent when focusing on each rule in separation, giving a possibility of generating more advantageous outcomes than those available by investing directly in the market or by using a single rule.

We empirically analyse the properties of combining three of the best known rules: the turn-of-the-month effect, the Halloween Effect and the moving average rule. All the rules have been known for many years in the academic literature and for longer by practitioners. Although the rules work well individually, we have not chosen them in a particular effort to maximize returns, but because they are well-known and form a parsimonious set. Some authors have shown that calendar effects are not always independent from each other (e.g., Lucy and Zhao, 2008, Swinkels and Van Vliet, 2012); hence, one should not necessarily expect sizable improvements in profitability when combining signals from several arbitrarily chosen calendar-based rules. However, other studies demonstrate an (at least partial) independence of calendar effects, implying a potential for improved profitability of strategies which combine signals from different rules: Atanasova and Hudson (2010) show that moving average rules are largely independent from many seasonal anomalies, and Haggard and Witte (2010) find the Halloween to be substantially independent from the January effect. Our approach of combining different rules aims at utilizing this independence among rules and could easily be generalized to combinations of other rules.

A wide variety of seasonal anomalies have been observed in financial markets for many years. The turn of the month effect (TOTM), whereby stock returns are substantially higher around the turn of the month, was reported by market experts such as Merrill (1966) and later in academic studies by Ariel (1987) and Lakonishok and Smidt (1988). Ariel considered the last trading day of the month and the first nine trading days of the next month whereas Lakonishok and Smidt consider the last trading day of the month and the first three trading days of the next month. Subsequent studies confirm the prevalence of this effect (e.g., Ogden, 1990; McConnell and Xu, 2008; Hudson and Atanasova, 2009).

The Halloween effect and the very closely related 'sell-in-May-and-go-away' effect, whereby stock returns are lower in the summer months, first explicitly appeared in the academic literature in a paper by Bouman and Jacobsen (2002), although Gultekin and Gultekin (1983) deal with closely related issues. However, as Bouman and Jacobsen make clear, this rule has been well known to market practitioners for many decades.

The technical analysis of securities is generally considered to be the earliest form of investment analysis. The oldest techniques date back at least to Charles Dow in the 1890s and many techniques have been in use since the 1930s or before (Brock et al. 1992). Despite its popularity with practitioners, technical analysis was largely dismissed by prominent academics for many years (Malkiel, 1981). However, Brock et al. (1992) gave empirical support for the approach by showing that simple moving average and trading range break-out rules outperform a buy-and-hold approach on the Dow Jones Index from 1897 to 1986.

There are a huge number of technical trading rules (see, e.g., Lo, Mamayski and Wang, 2000). However, the moving average rules used in the Brock et al. paper are very well known and have been the subject of the most academic scrutiny. Sullivan et al. (1999) find that the results are robust to data-snooping. The rules have also been shown to work in other equity markets (e.g., Hudson et al., 1996; Ratner and Leal, 1999) and for individual stocks (Bokhari et al., 2005), albert some evidence suggests that the performance of technical trading rules have largely diminished in the resent period (e.g., Shynkevich, 2012) or even did never exist when the data snooping bias and transaction costs are accounted for (Bajgrowicz and Scaillet, 2012). Nevertheless, given the extensive popularity and evidence on the effectiveness of these rules, we let the data speak for itself and use them for our investigations.

II. Data

We initially carry out our investigation on daily data for the Dow Jones Industrial Average Index from 3/23/1896 to 5/26/2009 to obtain a long term view of the interactions between the rules and to confirm that combining them can be advantageous. [1] We subsequently analyse a later period to investigate how the interactions among rules have been performing relatively recently and whether they are economically exploitable given realistic trading costs on low-cost instruments such as futures. As futures on the Dow index were not

[1] We do not extend the sample beyond March 2009, as the subsequent period was characterised by an increasing impact of unconventional monetary policy measures in the US; this would have affected the behaviour of the stock market in a way unprecedented in the modern history. Hence, the results in the most recent period could be different from those in the pre-QE era, an interesting issue to investigate but not the focus of this paper.

available for trading until 6th November 1997, in order to obtain a larger sample we instead investigate the profitability of trading in futures on S&P500 (large cap) index (available since 23rd April, 1982) on combined signals generated by the S&P500 itself.

III. Trading Strategy Design

Each of the rules divides the period under investigation into sub-periods when it is advantageous to buy (and stay long) and sub-periods when it is advantageous to sell (and stay short, or at least out of the market). Different combinations of the rules can be assessed by combining the sub-periods (i.e., buy and sell periods as indicated by each rule) in various ways. For example, we can consider the sub-periods when all of the rules give a buy signal or alternatively periods when all the rules indicate a sell, or perhaps when two of the rules give a buy signal and one of the rules a sell signal.

The moving average rules of Brock et al. (1992) operate as follows: buy (sell) signals occur when the short run moving price average, measured over past x days, is above (below) the long run moving average, measured over y past days, by an amount larger (smaller) than a band z. This is denoted as MA(x, y, z). The buy (sell) return for each day in the sample is calculated in accordance with these signals. In this study we illustrate the results from a MA(1,200,0) rule, although we have also examined other variants and the findings are robust.

The TOTM effect gives buy signals on four days around the turn of each month, beginning on the last trading day of the month and ending on the third trading day of the following month. The Halloween effect gives buy signals between the 31 October and the 30 April each year.

IV. Results

Table 1 shows how the rules have performed on an individual basis. Panel A shows for the DJIA index that the individual rules are highly predictive over the full sample period.

Table 1: Performance of Individual Rules

Rule:	MA(1,200) Buy days	MA(1,200) Sell days	Difference	Halloween	non Halloween	Difference	TOTM days	non TOTM days	Difference
Panel A: Dow Jones, full sample: 1896 - 2009									
Mean	0.0386	-0.0177	0.0563	0.0306	0.0058	0.0248	0.1166	-0.0029	0.1195
t-stat	6.1808	-1.3416	3.8610	3.5740	0.6397	1.9854	8.1263	-0.4186	7.5006
p-value	<0.00001	0.17974	0.00011	0.00035	0.52237	0.04711	<0.00001	0.67551	<0.00001
# days	19429	11196		15211	15613		5400	25424	
%pos	53.4768	50.0715	3.4053	52.2385	51.5596	0.6789	56.3333	50.9519	5.3815
SD	0.8706	1.3932		1.0551	1.1345		1.0541	1.1037	
Panel B: S&P500, futures trading sample: 1982-2009									
Mean	0.0428	-0.0079	0.0506	0.0505	0.0075	0.0430	0.0995	0.0119	0.0877
t-stat	3.4991	-0.2002	0.9892	2.6256	0.3637	1.0837	3.2501	0.7500	1.8887
p-value	0.00047	0.84133	0.32257	0.00865	0.71608	0.27851	0.00115	0.45326	0.05894
# days	4874	1916		3328	3462		1292	5498	
%pos	53.6110	50.8351	2.7759	53.2452	52.4263	0.8189	54.9536	52.3281	2.6254
SD	0.8539	1.7031		1.1085	1.2044		1.1003	1.1712	

Note: # days denotes the number of days in the sample for which a give rule generates a given signal; %pos denotes the fraction of days within each signal subsample (buy or sell) with positive returns; SD denotes standard deviation of returns.

For the moving average rule the returns in the buy periods are positive and highly significant, the returns in the sell periods are negative, and the difference between the returns in the buy and sell periods is positive and highly significant. In line with the literature, the percentage of days with positive returns during buy and sell periods has also been calculated. This measure also shows the difference between buy and sell periods to be positive, i.e., to some extent the MA rule successfully separates days with positive returns from those with negative ones. The Halloween rule has positive and highly significant returns in the buy period and much smaller and insignificant returns in the sell period. The difference between the returns in the buy and sell periods is positive and marginally significant. The percentage of positive returns gives similar conclusions as for the MA rule. The TOTM rule has large and highly significant positive returns in the buy period and negative although insignificant returns in the sell period. The difference between the buy and sell returns is positive and significant, with the magnitude similar to the results in McConnell and Xu (2008). The difference in the percentage of positive returns between the buy and sell periods is also positive.

Panel B of Table 1 looks at the results for the S&P500 index in a period starting in 1982, when futures on S&P500 were traded. For the moving average rule, the returns in the buy periods are positive and highly significant, the returns in the sell periods are negative although not significant, and the difference between the returns in the buy and sell periods is positive but not significant. There is, however, a substantial positive difference between the percentage of positive returns in the buy and sell periods. The Halloween rule has positive and highly significant returns in the buy period and smaller and insignificant returns in the sell period. The difference between the returns in the buy and sell periods is positive and insignificant. There is a modest difference in the number of positive returns in the buy and sell periods. The TOTM rule has large and highly significant positive returns in the buy period and much smaller although insignificant returns in the sell period. The difference between the returns in the buy and sell periods is positive and marginally significant. The difference in the percentage of positive returns in the buy and sell periods is substantial. Overall, these results indicate that each of the rules, especially the TOTM, was successful in the whole sample, but their profitability seems to have diminished in a period starting in 1982. These individual rules' results constitute a benchmark for profits generated by combinations of rules, as analysed below.

When testing multiple hypotheses on a set of data using a significance level α, the Null should be expected to be falsely rejected in α% of cases (type I error).[2] In our case, we conduct six tests of significance of returns (buy and sell returns for three rules), hence some of the rejections of the Null could be spurious. One way to address this issue is to apply the Bonferroni correction to control the familywise error rate, by testing each individual

[2] We thank the Editor for pointing this out.

hypothesis at a significance level of α /N, where N is the number of tests/hypotheses (Abdi, 2007). The Bonferroni correction is rather conservative and can lead to a high type II error rates, especially for higher values of N. In our case, α /N=.05/6=.00833 for 5% and .1/6=.01667 for 10% significance levels, respectively. The comparison of relevant p-values with those adjusted significance levels reveals that our original conclusions based on unadjusted α values stand, with only one exception (for Halloween returns in the futures trading sample and for α=.05).

Table 2 shows the results for all possible combinations of the three rules for the Dow Jones in the 1896 to 2009 period. If a rule generates a buy (sell) signal, this is denoted by 'Y' ('N') in the table's heading. For instance, 'YNY' states that both the moving average and the turn of the month rules generate a buy signal and the Halloween rule generates a sell signal. Panel A shows each of the individual combinations. Panel B groups of the combinations by the number of rules generating buy signals. In general terms, it is clear that combining the rules does tend to increase their predictive power. The mean return actually increases monotonically with the number of rules generating buy signals (Panel B). A similar monotonic increase also occurs in the percentage of positive returns as the number of rules generating buy signals increases. The returns when at least two rules give buy signals are always positive and highly significant. When three rules give a buy signal (denoted 'YYY'), the return is 0.1201%, which is larger than any rule achieves unconditionally (as reported in Table 1, Panel A). When only one rule gives a buy signal, the returns are not significant. When each rule gives a sell signal ('NNN'), we observe a significant negative return. At -0.0641%, this is much smaller than the returns on a sell day for any rule taken unconditionally (Table 1, Panel A). The difference between the return when all rules give a buy signal and when all rules give a sell signal ('YYY-NNN') is large at 0.1842% and highly significant.

Table 2: Performance of Combined Rules: Dow Jones (1896 – 2009)

Panel A: All Individual Combinations

MA(1,200)	Y	N	Y	Y	N	N	Y	N	YYY-NNN
Halloween	Y	Y	N	Y	N	Y	N	N	
TOTM	Y	Y	Y	N	Y	N	N	N	
Mean	0.1201	0.1089	0.1393	0.0301	0.0697	-0.0178	0.0088	-0.0641	0.1842
t-stat	5.9207	2.5494	7.0363	3.1479	1.5843	-0.9306	0.8819	-2.9003	6.1411
p-value	<0.00001	0.01080	<0.00001	0.00165	0.11314	0.35207	0.37784	0.00373	<0.00001
# days	1682	1010	1747	7683	929	4770	8317	4487	6169
%pos	56.54	56.14	58.33	52.67	54.36	49.92	52.58	47.98	
SD	0.8320	1.3573	0.8277	0.8375	1.3408	1.3232	0.9134	1.4796	

Panel B: Combinations Grouped by the Number of Rules Used

MA(1,200)	Y	any two Ys	any one Y	N	YYY-NNN
Halloween	Y			N	
TOTM	Y			N	
Mean	0.1201	0.0560	0.0038	-0.0641	0.1842
t-stat	5.9207	6.3528	0.4082	-2.9003	6.1411
p-value	<0.00001	<0.00001	0.68313	0.00373	<0.00001
# days	1682	10440	14016	4487	6169
%pos	56.54	53.96	51.79	47.98	
SD	0.8320	0.9004	1.1002	1.4796	

Note: # days denotes the number of days in the sample for which a give rule generates a given signal; %pos denotes the fraction of days within each signal subsample (buy or sell) with positive returns; SD denotes standard deviation of returns.

It is also interesting to note that the higher returns generated by combining different rules are not related to an increased standard deviation of returns: the standard deviation of returns when all three rules give a buy signal is the lowest of any of the combinations at 0.832% whereas the standard deviation of returns when all three rules give a sell signal is the highest of any of the combinations at 1.4796%. In fact, the standard deviation of returns decreases monotonically in line with the number of buy signals generated (Panel B). Thus, it seems that the superiority of profits from combined rules is not explained by this conventional measure of risk. The analysis of S&P500 index in the 1982 to 2009 period generates results which are qualitatively very similar to those for the DJIA investigated over the longer period (results available on request). In addition, these results are robust to the aforementioned Bonferroni correction, with the adjusted significance values taking into account that eight (four) hypotheses are being tested in Panel A(B) of Table 2 and using adjusted significance values of .00625 and .01250 (.01250 and .02500) instead of the original significance levels of 5% and 10%, respectively. When compared against the p-values reported in Table 2, all of the original conclusions regarding significance of our results remain unchanged, with only one exception (for NYY rule at α=.05). Hence, our initial inference is robust to the multiple hypotheses issue.

Overall, these findings show that combining the trading rules gives significant increases in the ability to predict returns and that higher predicted returns are not accompanied by higher risk. These findings suggest the possibility of existence of profitable trading strategies combining signals from then one rule. Table 3 shows the results of implementing trading strategies using rule combinations on recent data, when futures contracts were available on the index. Trading is conducted in futures on the S&P500 Index using buy-and-sell signals based on the same index. We use S&P500 rather than DJIA for trading since, firstly, futures on the former were traded since 1982 and on the latter only since 1997, giving 15 years more of observations, and, secondly, the MA(1,200) rule in DJIA Index was reversed in the post-1997 period, resulting in trading signals leading to losses (results not reported to preserve space). Futures contracts are substantially cheaper to trade than either exchange-traded funds or portfolios of stocks tracking the index and so are more likely to produce profitable trading strategies net of transaction costs. We calculate the results of applying a “double or out” trading strategy following Bessembinder and Chan (1998) to various combinations of the rules. The neutral position is to hold the index (futures contract in our case). If a buy day is indicated, the investment in the index is doubled whereas, if a sell day is indicated, the funds are invested in bonds, thus giving broadly similar risk to a buy and hold strategy (the exact standard deviations are reported in the table). We use data on 3-Month T-Bills secondary market rate from Fed St Louis as a proxy for risk-free bond investment.

Profits from trading on combinations of rules (Table 3, row 1) outperform the buy-and-hold strategy applied to the index futures (row 2) when operating individually and also when at least two rules generate buy signals (if trading costs are not allowed for). There is a general decline in the annualized average returns as the number of rules generating buy signals declines. The average number of trades per year (row 4) and break-even transaction costs (row 5) are also shown in Table 3. The later measures how high the transaction costs would have to be to completely offset the profits, hence the lower they are the lower the net-of-transaction-costs strategy returns would be for a given level of transaction costs. For individual rules, strategies that involve frequent trading such as the TOTM rule do relatively less well (i.e., have lower break-even transaction costs) whereas rules which involve little trading such as the Halloween rule do relatively better. However, lower trading costs and higher excess returns seem to be obtainable at a cost of higher volatility risk (row 6), as compared to the volatility of buy-and hold strategy (row 7). Trading costs for futures quoted in the literature vary from 0.05% to 0.5% (Chen et al., 2009), hence many of these rules could potentially generate excess profits even given realistic trading costs (rows 9-10). For instance, the table reports that at transaction costs of 0.25% the MA(1,200) and the Halloween rule would yield net return of 2.86% and 3.88%, respectively.

As for the combinations of rules, buying when all three rules generate a buy signal ('YYY') yields the highest profits and break even transaction costs, whereas relying on fewer buy signals results in lower profits and break-even transaction costs. Hence, combining buy signals of these three different rules seems to increase the net profitability of the trading strategy. These high profits are accompanied by lower volatility, which further highlights the beneficial effect of combining three trading rules. At transaction costs of 0.25%, only the rule based on three simultaneous buy signals ('YYY') would yield positive excess returns, at

Table 3: Profits from double-or-out strategy from trading in S&P500 futures (26 April 1982 -23 March 2009)

Panel A: All Individual Combinations

MA(1,200) Halloween TOTM	Row	Y Y Y	N Y Y	Y N Y	Y Y N	N N Y	N Y N	Y N N	N N N	MA(1,200)	Halloween	TOTM
Annualised average returns strategy (in %)	1	11.6658	9.7282	10.3168	8.0637	6.1985	3.9454	4.5340	2.5964	13.1871	12.0098	16.5161
Annualised average B&H returns S&P500 futures (in %)	2	7.1311	7.1311	7.1311	7.1311	7.1311	7.1311	7.1311	7.1311	7.1311	7.1311	7.1311
Excess return over B&H SP500 futures average	3	4.5347	2.5971	3.1857	0.9326	-0.9326	-3.1857	-2.5971	-4.5347	6.0559	4.8787	9.3850
Average number of trades per year	4	8.2392	7.7938	8.1278	7.4598	7.4598	8.1278	7.7938	8.2392	6.3835	2.0041	23.9753
Break-even transaction costs	5	0.2752	0.1666	0.1960	0.0625	-0.0625	-0.1960	-0.1666	-0.2752	0.4743	1.2171	0.1957
Annualised standard deviation of trading strategy returns	6	282.0962	320.4894	314.3368	382.9346	320.8239	392.9265	386.5446	460.7953	400.4686	411.4222	264.4038
Annualised standard deviation B&H S&P500 futures	7	323.5574	323.5574	323.5574	323.5574	323.5574	323.5574	323.5574	323.5574	323.5574	323.5574	323.5574
Sharpe ratio	8	0.0414	0.0304	0.0328	0.0211	0.0193	0.0100	0.0117	0.0056	0.0329	0.0292	0.0625
Realised excess net return p.a. (assuming TC of 0.05)	9	3.7108	1.8177	2.3729	0.1866	-1.6786	-3.9985	-3.3765	-5.3587	5.4176	4.6783	6.9874
Realised excess net return p.a. (assuming TC of 0.25)	10	0.4152	-1.2998	-0.8782	-2.7973	-4.6625	-7.2496	-6.4940	-8.6543	2.8642	3.8767	-2.6027
Jensen's alpha (p-value)	11	0.0169 (0.064)	0.0033 (0.690)	-0.0016 (0.847)	-0.0089 (0.235)	-0.0111 (0.184)	-0.0227 (0.002)	-0.0224 (0.005)	-0.0410 (0.004)	0.0282 (0.056)	-0.0147 (0.001)	0.0516 (<0.001)

Table 3 continued

Panel B: Combinations Grouped by the Number of Rules Used

MA(1,200) Halloween TOTM	Row	Y Y Y	any two Ys	any one Y	N N N
Annualised average returns strategy (in %)	1	11.6658	13.8465	0.4157	2.5964
Annualised average B&H returns S&P500 futures (in %)	2	7.1311	7.1311	7.1311	7.1311
Excess return over B&H SP500 futures average	3	4.5347	6.7154	-6.7154	-4.5347
Average number of trades per year	4	8.2392	23.1588	23.1588	8.2392
Break even transaction costs	5	0.2752	0.1450	-0.1450	-0.2752
Annualised standard deviation of trading strategy returns	6	282.0962	372.4969	444.2182	460.7953
Annualised standard deviation of B&H S&P500 futures	7	323.5574	323.5574	323.5574	323.5574
Sharpe ratio	8	0.0414	0.0372	0.0009	0.0056
Realised excess net return p.a. (assuming TC of 0.05)	9	3.7108	4.3995	-9.0313	-5.3587
Realised excess net return p.a. (assuming TC of 0.25)	10	0.4152	-4.8640	-18.2948	-8.6543
Jensen's alpha (p-value)	11	0.0169 (0.064)	0.0299 (0.035)	0.0131 (0.410)	-0.0410 (0.004)

0.42%. Furthermore, as reported in Table 3, Panel B, trading on three buy signals, rather than just (any) two or one, generates the highest break-even transaction costs and realized net returns (assuming transaction costs of 0.25%).

However, the picture of benefits from combining three independent trading rules is not unambiguous: each of these rules, when used individually, generates higher excess returns and two of them (MA and Halloween) also higher break even transaction costs than even the most profitable combination of rules. However, these higher profits are accompanied by higher volatility, which in turn makes the strategy of trading on combination of rules more attractive. In fact, the Sharpe ratio (row 8) for the YYY rule is higher than those for MA and Halloween-based strategies, and while it is lower than the one for TOTM, the latter is characterized by much lower break-even transaction costs than those for the YYY rule. Hence, no rule is strictly dominant and for traders with relatively high transaction costs and poorly diversified portfolios (when total volatility risk matters), the YYY rule could well be the optimal choice.

We further investigate to what extent the gross profits obtainable from trading strategies are simply a compensation for risk. To this end, we employ the Carhart (1997) model using data on risk factors obtained from Prof. Kenneth French's website. The model provides the measurement of Jensen's alpha for each trading strategy, which is reported in the last row of Table 3. The results confirm the finding reported for risk-unadjusted returns that combining more buy signals within one strategy yields higher (risk-adjusted) profits, e.g., the Jensen's alpha is a significant 0.017 for the YYY strategy and declines as fewer buy signals are used, being the lowest for the NNN strategy (a significant negative value of -0.041). When used individually, the MA and TOTM effects still outperform the market by yielding positive (risk-adjusted) profits, whereas the Halloween effect seems to significantly underperform the market. The latter finding complements the previous observation that the Halloween effect was found to generate the lowest gross returns accompanied by the highest volatility risk. When the number but not the specific combinations of buy signals is considered (Table 3, panel B), the pattern of risk-adjusted returns is broadly similar to the one for gross returns, i.e., the combination of all effects yields a second-best outcome, after the strategy which utilizes any two signals. Lastly, similarly to the risk-unadjusted results, two of the individual rules (MA and TOTM) yield higher Jensen's alphas than even the most profitable combination of rules (YYY). However, profits from one of these individual rules (MA) suffer from higher return volatility, whereas the other rule (TOTM) is associated with lower break-even transaction costs.

In summary, a combination of rules can be an attractive investment strategy, depending on the individual trader's transaction costs and the degree of diversification of their portfolio, as the later determines whether the total volatility risk or only the systematic risk is relevant to them: when transaction costs are low, a TOTM-based strategy appears to be superior regardless of the diversification level, and the MA(1,200) rule generates superior results for well diversified traders with high costs. However, for a typical individual investor, i.e., with high transaction costs and only a few stocks in their portfolio, combining three rules yields the best results.

V. Conclusion

Although there is a large literature on trading rules and seasonal anomalies, surprisingly, there is very little work on the potential benefits of combining these effects. In this paper, we demonstrate the potential advantages of the latter approach by combining some of the best known effects from the literature. Combining trading rules yields certain benefits, especially if we consider poorly diversified traders who face high transaction costs, i.e., typical individual investors. Whilst we have used three well known rules, the approach of combining individual rules can easily be generalized to any combination of rules, and could potentially result in an even more superior performance. Further improvements could potentially be achieved by (possibly time-varying) weighting of signals generated by each component rule. In theoretical terms, our findings can add to the understanding of the properties of asset markets and in particular to the literature on efficient markets, which has previously neglected the combination of established market effects. It is apparent that rule combinations can potentially add value by allowing the optimum timing of trades. From the evidence we have provided it also seems that rule combinations can be profitable for trading in their own right given realistic trading costs. In summary, it is clear that combining anomalies and trading rules is of great interest from both theoretical and practical viewpoints. An important avenue for future research is to consider how one might seek to optimize the vast number of potential combinations of trading rules whilst guarding against the pitfalls of data mining. There are a least two broad potential approaches: create a large number of rules and systematically investigate the effects of combining them (White, 2000), or, alternatively, use an approach that can generate new rules by combining existing rules, which is a process fairly similar to that used in Intelligent Agent Modelling (see, for example, Manahov et. al., 2014).

References

Abdi, H., 2007, Bonferroni and Šidák corrections for multiple comparisons, in: Salkind, N. J., Encyclopedia of Measurement and Statistics. Thousand Oaks, CA: Sage.
Ariel, R. A., 1987, A monthly effect in stock returns, *Journal of Financial Economics*, 18, 161-174.
Atanasova, C. V., and R. S. Hudson, 2010, Technical trading rules and calendar anomalies – Are they the same phenomena?, *Economics Letters*, 106, 128-130.
Bajgrowicz, P., and O. Scaillet, 2012, Technical trading revisited: False discoveries, persistence tests, and transaction costs, *Journal of Financial Economics*, 106, 473-491.
Bessembinder, H., and K. Chan, 1998, Market efficiency and the returns to technical analysis, *Financial Management*, 27, 2, 5-13.
Bokhari, J., C. Cai, R. Hudson, and K. Keasey, 2005, The predictive ability and profitability of technical trading rules: Does company size matter?, *Economics Letters*, 86, 21-27.
Bouman, S., and B. Jacobsen, 2002, The Halloween indicator, 'sell in May and go away': Another puzzle, *American Economic Review*, 92, 5, 1618-1635.
Brock, W., J. Lakonishok, and B LeBaron, 1992, Simple technical trading rules and the stochastic properties of stock returns, *The Journal of Finance*, 47, 5, 1731-1764.
Carhart, M. M, 1997, On persistence in mutual fund performance, *Journal of Finance*, 52, 1, 57-82.
Chen, W., R. K. Chou, and H. Chung, 2009, Decimalization, ETFs and futures pricing efficiency, *The Journal of Futures Markets*, 29, 2, 157-178.
Dzhabarov, C., and W.T. Ziemba, 2010, Do seasonal anomalies still work?, *The Journal of Portfolio Management*. 36, 3, 93-104.
Gultekin, M.N., and N. Gultekin, 1983, Stock return seasonality: International evidence, *Journal of Financial Economics*, 12, 469-481.
Haggard, K.S., and H.D. Witte, 2010, The Halloween effect: Trick or treat?, *International Review of Financial Analysis*, 19, 379-387.
Hudson R., M. Dempsey, and K. Keasey, 1996, A note on the weak form efficiency of capital markets: The application of simple technical trading rules to UK stock prices - 1935 to 1994, *Journal of Banking and Finance*, 20, 1121-1132.
Hudson, R. S., and C. V. Atanasova, 2009, Equity returns at the turn of the month: Further confirmation and insights, *Financial Analysts Journal*, 65, 4, 14-16.
Lakonishok, J., and S. Smidt, 1988, Are seasonal anomalies real? A ninety-year perspective, *Review of Financial Studies*, 1, 403-425.
Lo, A. W., H. Mamaysky, and J. Wang, 2000, Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation, *Journal of Finance*, LV, 4, 1705-1765.
Lucy. B. M. and S. Zhao, 2008, Halloween or January? Yet another puzzle, *International Review of Financial Analysis*, 17, 1055-1069.
Malkiel, B., 1981, A random walk down Wall Street, 2nd ed. Norton, New York.
Manahov, V., R. Hudson, and B. Gebka, 2014, Does high frequency trading affect technical analysis and market efficiency? And if so, how? *Journal of International Financial Markets, Institutions & Money*, 28, 131-157.
McConnell, J. J., and W. Xu, 2008, Equity returns at the turn of the month, *Financial Analysts Journal*, 64, 2, 49-64.
Merrill, A. A., 1966, Behavior of prices on Wall Street, Chappaqua, NY: The Analysis Press.
Ogden, J. P., 1990, Turn-of-month evaluations of liquid profits and stock returns: A common explanation for the monthly and January effects, *Journal of Finance*, XLV, 4, 1259-1272.

Park, C., and S. H. Irwin, 2007, What do we know about the profitability of technical analysis?, *Journal of Economic Surveys*, 21, 4, 786-826.

Ratner, M., and R.P.C. Leal, 1999, Tests of technical trading strategies in the emerging equity markets of Latin America and Asia, *Journal of Banking and Finance*, 23, 1887-1905.

Shynkevich, A., 2012, Performance of technical analysis in growth and small cap segments of the US equity market, *Journal of Banking & Finance*, 36, 193-208.

Sullivan, R., A. Timmermann, and H. White, 1999, Data-snooping, technical trading rule performance, and the bootstrap, *Journal of Finance*, LIV, 5, 1647-1691.

Swinkels, L. and P. Van Vliet, 2012, An anatomy of calendar effects, *Journal of Asset Management*, 13, 271-286.

White, H., 2000, A reality check for data snooping, *Econometrica*, 68, 1097- 1126.