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SIMPLE MOVING AVERAGE AS A RISK MANAGEMENT METHOD IN MAIN ASSET CLASSES

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Abstract. As during turbulent market conditions correlations between main asset classes falter, investors are forced to experience times of high uncertainty which in most cases may lead to irrational decisions. This problem stimulates search for non-discretionary risk management methods. The aim of the paper is to test if concept of SMA can be used in such role. The investigation is based on studying historical prices of various asset classes; statistical data analysis method is used. Results of this study reveal that SMA method when used as a trend indicator for main stock and REIT indices can significantly reduce standard deviation and maximum drawdown measures.

Keywords: risk management, asset classes, tactical asset allocation, moving averages, strategy, methods.

Jel classification: G02, G11, G14, G15

1. Introduction

Recent decade proved to be one of the most problematic periods for asset managers since great depression. Global economy suffered two recessions where the recent one which started in 2008 due to it's large impact to global markets is often being pronounced as the Great recession. As a result almost all main financial markets felt turbulence not only in terms of high volatility but also in maximum drawdown measures not seen for a very long time.

The Capital Asset Pricing Model (CAPM) explains security prices by assuming rational behaviour on the part of investors (Sharpe 1964). Components of this behaviour, like mean-variance optimization, suggest investors must be able to solve complicated equations to construct optimal portfolios (Bodie *et al.* 2008). However there are many articles with arguments that this concept is fragile (Michaud 1989; Farrelly 2006). As correlations during the peak of high economic uncertainty between main asset classes brake down (Taleb 2007; Campbell *et al.* 2002), rational behaviour is replaced by panic so even supposed to be well-diversified (rational) investors are experiencing huge losses in their investment portfolios (Dalbar 2010; Coaker 2007; Kindleberger, Aliber 2005; Lowenstein 2001; Shiller 1984).

This eventually awakes discussions about effective asset management strategies which should provide not only robust classical risk reward ratios (where standard deviation is assumed to be main risk measure) but also help investment managers and investors avoid large peak-to-trough drawdowns.

If we assume that systematic irrationality in the financial markets is one of the main factors that stimulate widening the scale of boom-bust cycles it is natural to look for such risk management methods in areas related to behavioural finance. Thus for our analysis we will borrow principles of discipline, called technical analysis (TA) where concept of simple moving averages (SMA) is among most popular trend following techniques.

Investment community almost unanimously agree that diversification is one of the main factors influencing final portfolio results (Bernstein 2010; Faber and Richardson, 2009; Darst 2007; Gibson 2007; Gibson 2007; Fraser-Sampson 2006; Bogle 2001; Jacquier and Marcus, 2001; Ibbotson *et al.* 2000) so it is very important to look for risk management strategies that add value not in one particular asset class but ideally in all main risk driven asset classes added to the portfolio. While still largest portion of articles focus primarily on stocks, in this paper together with stocks we will also analyse assets like real estate and commodities. We will examine if using SMA filter for such asset classes can help lowering risk and if so what is the significance of that result.

2. Literature review on concept of technical analysis and moving averages

The moving average technique goes back to at least 1930s (Brock *et al.* 1992) and is one of the most widely used methods of technical analysis (TA). Technical analysis can be described as the various stock market forces interactions and their impact on share prices survey (Dzikevičius, Šaranda 2010). The crowd of TA supporters is quite impressive and according to Taylor and Allen (1992) about 90% of market participants place some weight in TA. Similar survey by Mizrach and Weerts (2007) led to conclusion that 52% of semi-professional traders use simple moving average rules.

TA users think that it is possible to predict development of events in future using historical data about stocks and market. Norvaišienė (2005) explains that TA factors are related to stock market conditions and are mainly focused on price changes, market volume, the demand and the supply of the stocks. So, the main reasoning of technical analysis supporters‘ could be determine as importance of historical analysis of stock rates that allow to ascertain cyclicality and future trends of a specified stock price making investment decisions (Jurevičienė, Albrichtaitė 2010).

Growing stock market and rising activity of investors attracts more increasing attention by retail traders who look for simple investing methods (Dudzevičiūtė, 2004). The MA technique is very easy to use and it's application in real life investing decision-making situations requires almost no profound knowledge. According to www.brokerreviews.com, in today's market almost all investment brokers give investors trading tools with already implemented technical analysis indicators. This makes TA even more popular where such methods like simple moving averages can be easily back tested and their attributes empirically evaluated.

TA is being used widespread although it's assumptions contradict to classical economic theories as having no basis (Dzikevičius, Šaranda, 2010). Brock, Lakonishok and LeBaron (1992) reviewed the literature on Technical Analysis issue and concluded that it has no statistical validity. Dzikevicius, Saranda and Kravcionok (2010) after testing SMA rules in stock market concluded that this method of forecasting is not accurate and cannot predict the right future stock prices. On the other hand, Jeremy Siegel (2008) in his book „Stocks for the Long Run"investigates the use of the 200 day SMA in timing the Dow Jones Industrial Average (DJIA) from 1886–2006, and contrary to previously cited findings, he concluded that even after adjusting for taxes, bid - ask spread and commissions, such simple market timing improves the absolute and risk - adjusted returns over a buy-and-hold of the DJIA. Faber and Richardson (2009) also analyzed simple moving averages using monthly data on various indices and too concluded that this method can add value to risk adjusted returns.

3. Data, rules specifications and methodology

This paper is focused on one of the most popular technical analysis indicators - simple moving average (SMA) and it's ability to act as a risk managing method for main asset classes: stocks, real estate and commodities (bonds are not included because we consider it as a safe instrument where additional risk management is not so necessary). We used monthly data series (closing prices for the month; provided by Bloomberg, MSCI Barra and NAREIT) and operated with following indices (used periods are shown in brackets):

Stocks:

− US stocks – *MSCI US Broad Market Index* (1970/01-2011/12).

− EAFE (Europe, Australasia and Far East) stocks – MSCI EAFE Net Return USD Index (1970/01-2011/12).

Real estate:

− FTSE NAREIT Index (1972/01-2011/12).

Commodities:

− S&P GSCI (Goldman Sachs Commodity Index) Total Return index (1970/03-2011/12).

As for a first step in our analysis we will calculate simple moving averages (SMA) using following formula:

$$SMA = \frac{\sum_{t=1}^{n} Y_t}{n}, \tag{1}$$

where:

$\sum_{t=1}^{n} Y_t$ – is the sum of the index prices for the time period n (in our case we will calculate all moving averages with periods starting from 2 to 20 months with a step of 1 month).

SMA is often considered as a trend indicator so the main rule (method) of it's usage is very intuitive – *hold risky assets in portfolio only when its' prices are higher than their SMA values (uptrend) and stay out of the market when prices are lower than their SMA values (downtrend).*

In this paper we will compare risk in downtrending periods (when prices are lower than their

SMA values) against risk in uptrending periods (when prices are higher than their SMA values).

In order to properly examine this issue we will compare periods of 2 to 20 months length that follow after those points of time when index price is lower than SMA value and higher than SMA value. In this test we will calculate what average standard deviations (monthly) and average MDD are during those periods.

While standard deviation (SD) is well-known and broadly used volatility/risk measure in various models, the MDD is somehow put aside.

The definition of MDD is very intuitive. Let the $P(t)$ be price of a given index at period *t* and $P_{\max}(t)$ the overall maximum of all prices up to this point in time:

$$P_{\max}(t) = \max_{\tau \leq t} P(\tau), \tag{2}$$

The MDD evaluated at time *T* is then defined as:

$$MDD = MDD(T) = \max_{t \leq T} \{P(t)/P_{\max}(t) - 1\}, \tag{3}$$

The MDD is simply the loss suffered when the position is opened at a local price maximum, and sold at the next local minimum.

As Vanguard's article (2011) shows, investors' behaviour during turbulent market conditions in 2001−2003 and 2007−2009 is noticeably irrational. Data from net cash flows to bond and equity mutual funds reveals that investors just before the crisis allocate significantly larger amounts of cash to equity funds than they do that in the middle or in the bottom of the crisis. As a matter of fact, in 2009 net flow of cash to equity funds was negative which indicates that instead of being rational and willing to buy stocks at significantly lower valuations than seen in 2007, majority decided to sell. This irrationality can be explained by behavioural aspects where one of them is element of fear and panic. The main idea behind adding MDD to our analysis is that by analyzing and considering methods that might have potential in helping managing maximum drawdowns, investors could avoid such irrational behaviour.

Finaly, when downtrend and uptrend points in time are filtered and averages of SD and MDD in following periods (2 to 20 months) are calculated, we will analyze the difference of findings in these two situations (risk in downtrend vs risk in uptrend). To evaluate the significance of these results we will use Welch's t test:

$$t = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2}}}, \tag{4}$$

where:

$\overline{X}_1$ – sample mean,

s_i^2 – sample variance,

N_1 – sample size

The degrees of freedom ν associated with this variance estimate is approximated using the Welch-Satterthwaite equation:

$$\nu = \frac{\left(\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2}\right)^2}{\frac{s_1^4}{N_1^2 \nu_1} + \frac{s_2^4}{N_1^2 \nu_1}} = \frac{\left(\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2}\right)^2}{\frac{s_1^4}{N_1^2 (N_1 - 1)} + \frac{s_2^4}{N_2^2 (N_2 - 1)}} \tag{5}$$

Here $\nu_i = N_i - 1$, the degrees of freedom associated with the i^{th} variance estimate.

4. Analysis

In this section we perform analysis of obtained test results and discuss their meaning and significance.

4.1. US stocks

Our first asset class that we examine is stocks and we start with US stocks which are represented by *MSCI US Broad Market Index*. Difference between average SD in the periods that come next after SMA is showing that US stocks are in downtrend with average SD in the periods that come next after SMA is showing that US stocks are in uptrend is presented in figure 1.

Results show that absolutely all periods that follow downtrend situations have higher on average standard deviation (SD) then those in uptrend. The biggest differences we locate in those situations when period for SMA calculation is between 9-20 months. We should note that these results are significant (p - value < 0.05).

Next we look at results with drawdowns (MDD) displayed in figure 2. We see that the depth of average maximum drops of the US stock price index in downtrend compared to uptrend increases significantly. The biggest differences we locate in those areas where period used for SMA calculation is 9-20 months and holding period is between 8-19 months (maximum drawdowns on average increase 6-8 %).

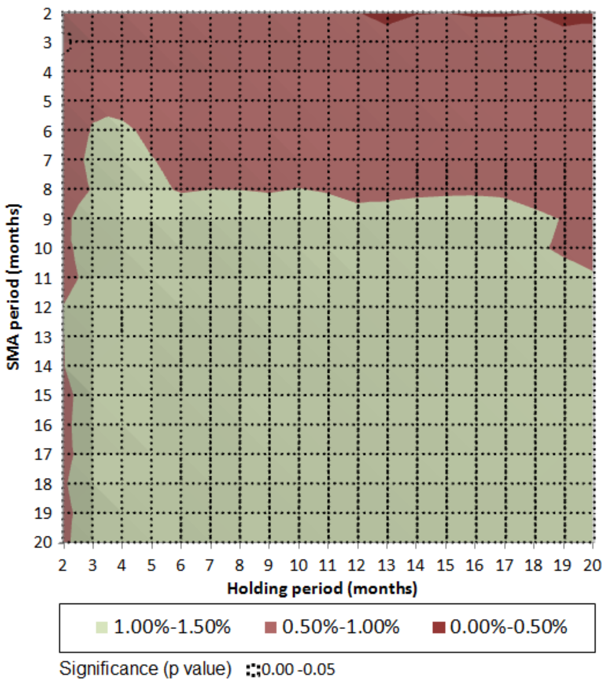

Fig.1. Difference between average SD in various holding periods when US stocks (1970/01-2011/12) are in downtrend and uptrend (Author's calculation).

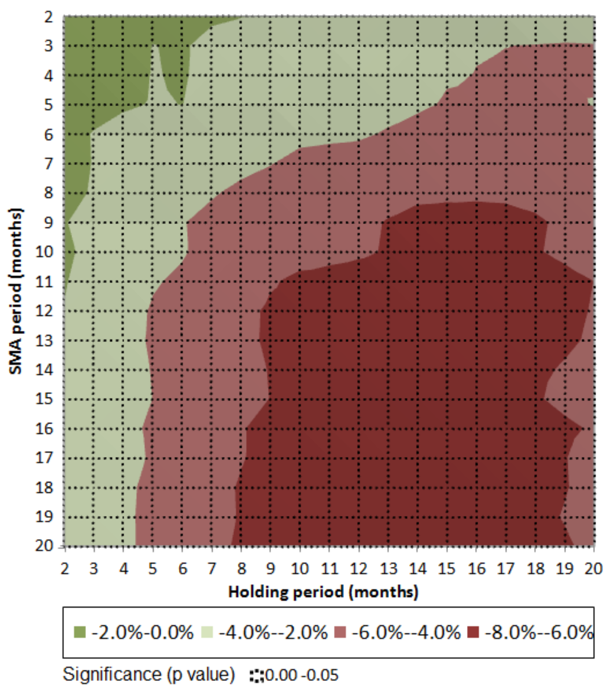

Fig.2. Difference between average MDD in various holding periods when US stocks (1970/01-2011/12) are in downtrend and uptrend (Author's calculation).

4.2. EAFE stocks

Our next step is EAFE stocks which are represented by *MSCI EAFE Net Return USD Index*. Difference between average standard deviations of holding periods in uptrend and downtrend are shown in figure 3.

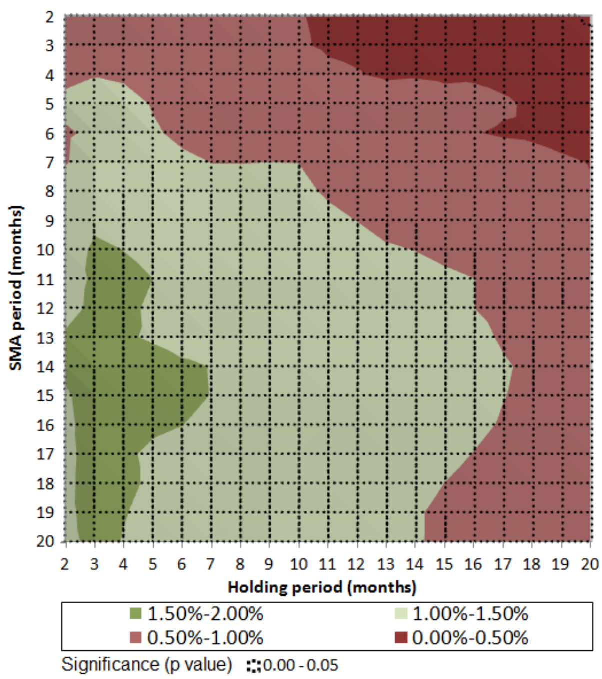

Fig.3. Difference between average SD in various holding periods when EAFE stocks (1970/01-2011/12) are in downtrend and uptrend (Author's calculation).

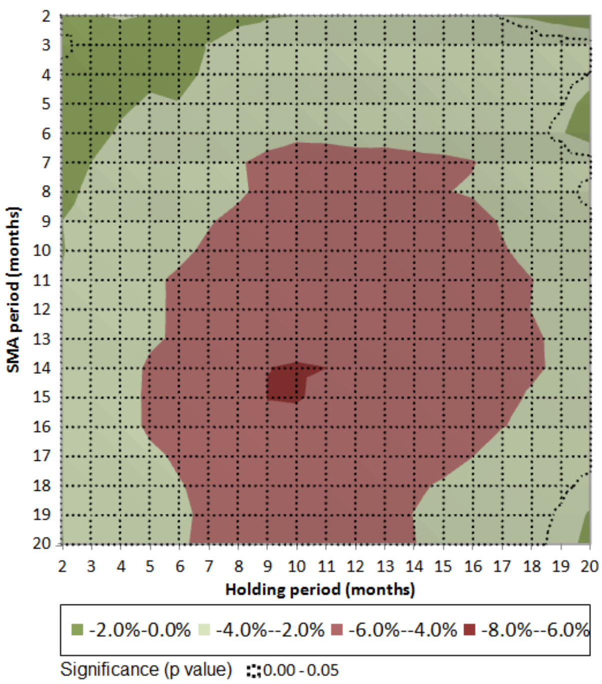

Fig.4. Difference between average MDD in various holding periods when EAFE stocks (1970/01-2011/12) are in downtrend and uptrend (Author's calculation).

As we see, here average standard deviations are also higher in downtrending moments than in situations where SMAs show uptrend. We must notice that widest difference appears in shorter term (2-5) holding periods and this happens when using longer term SMAs (10-20 months).

From data shown in figure 4 we observe that bigger drawdowns on average accur in downtrends (when compared to uptrends). This difference varies from 0.74 % to 6.05 % (p - value < 0.05).

4.3. Real estate

It should be noted that real estate investment trusts (REITs) are not a direct proxy for real estate and combine features of both equity and fixed income, but because there have not been any alternative investable indexes historically, we use the REIT index here which is provided by National Association of Real Estate Investment Trusts (NAREIT).

From data shown in figure 5 we can clearly see that similarly to stock indices on average bigger drawdowns strike in situations when FTSE NAREIT index is in downtrend (when compared to uptrend). This is pretty stable with all holding periods and with longer term SMAs these differences between average standard deviations steadily increase.

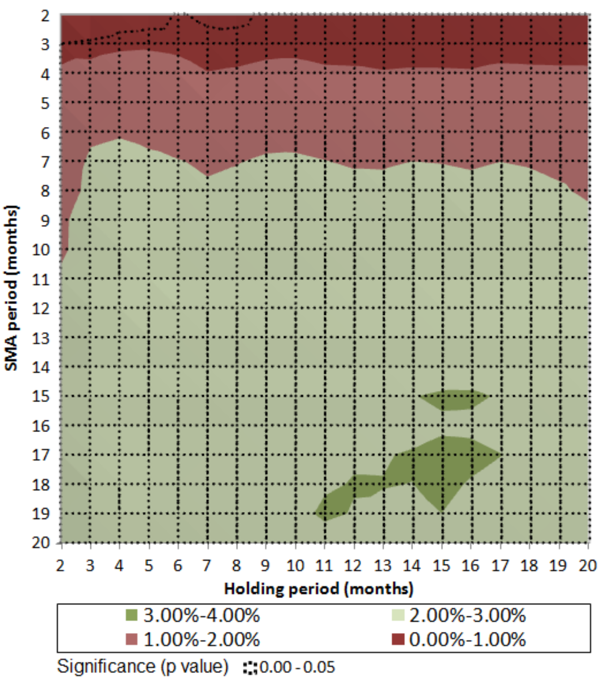

Fig.5. Difference between average SD in various holding periods when *FTSE NAREIT Index* (1972/01-2011/12) is in downtrend and uptrend (Author's calculation).

By looking at average MDD results shown in figure 6 we notice that in downtrending markets REIT prices fall much more than in uptrending times. The differences in this case are very significant (p - value < 0.01) and in majority of variants exceed 5% threshold. Furthermore, if investor chooses to use 10-20 months simple moving average (SMA) as a risk management method, he might reduce his drawdowns (assuming he only invests in REITs) on average by more than 10 % if he simply stays out of the market during downtrends.

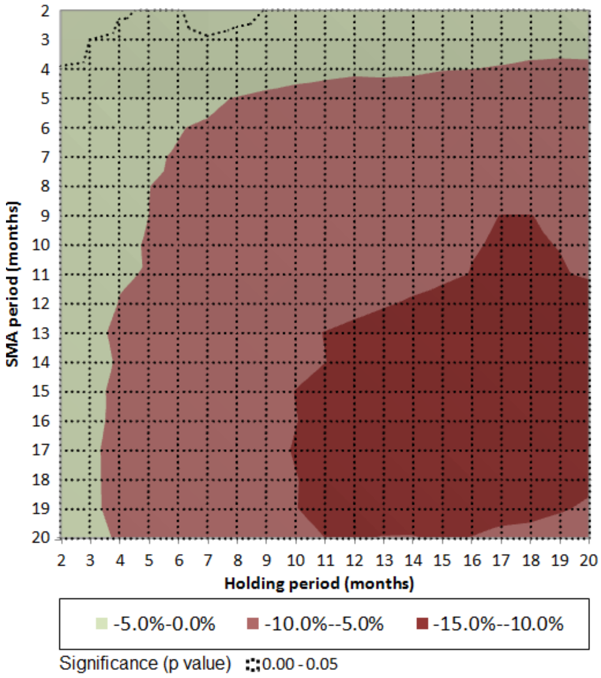

Fig.6. Difference between average MDD in various holding periods when *FTSE NAREIT Index* (1972/01-2011/12) is in downtrend and uptrend (Author's calculation).

4.4. Commodities

In order to perform our analysis on commodities we used S&P GSCI Total Return (TR) index.

GSCI is a world-production weighted index that is based on the average quantity of production of each commodity in the index, over the last five years of available data. This allows the S&P GSCI to be a measure of investment performance. Another good reason to use it in such test is because this index is tradable and is readily available to market participants of the Chicago Mercantile Exchange. Furthermore, retail investors can follow this index by simply buying and holding iShares S&P GSCI Commodity-Indexed Trust which is designed to replicate S&P GSCI TR index.

Difference between average SD in the periods that come next after SMA is showing that GSCI is in downtrend with average SD in the periods that come next after SMA is showing that GSCI is in uptrend is presented in figure 7. Comparing these results with cases of stocks and REITs, here we see a completely different picture. Standard deviation on average is lower in downtrend situations than in uptrends. In the area where 2-8 months SMA was used this difference is minimal and lacking statistical siginificance, but when we look in variants where periods for SMA calculation where longer than 8 months and holding periods exceeded 3 months calculated results are very significant (p - value < 0.01).

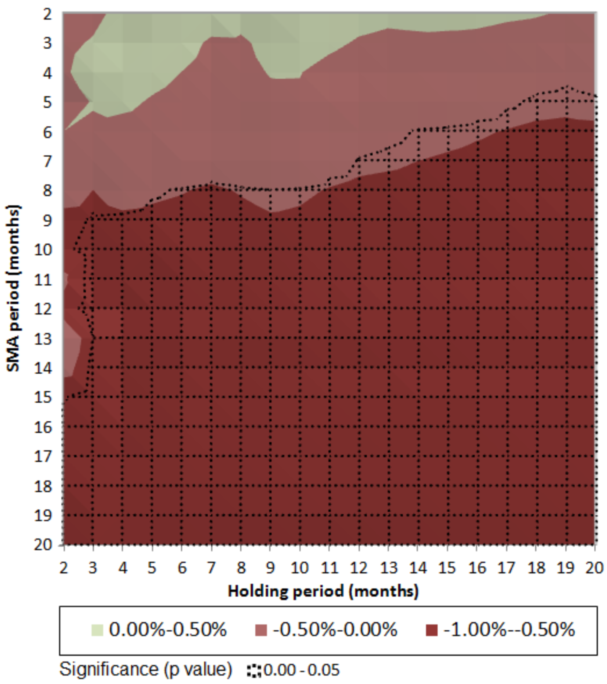

Fig.7. Difference between average SD in various holding periods when *S&P GSCI Total Return index* (1970/03-2011/12) is in downtrend and uptrend (Author's calculation).

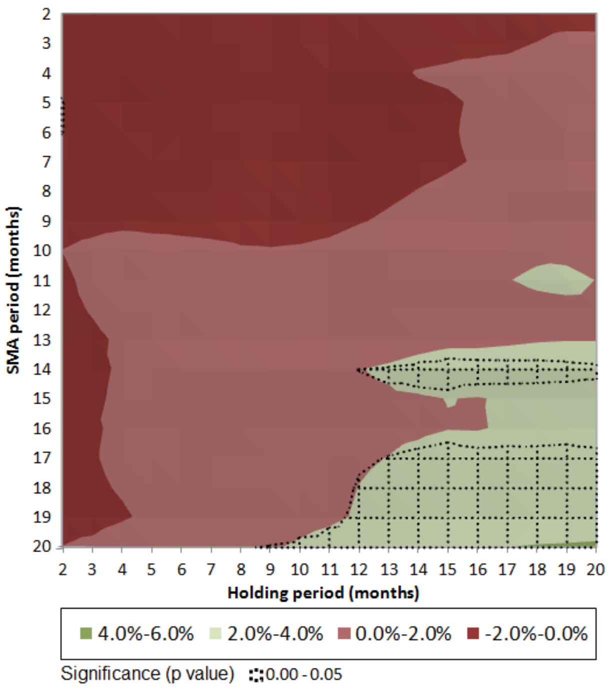

Fig.8. Difference between average MDD in various holding periods when *S&P GSCI Total Return index* (1970/03-2011/12) is in downtrend and uptrend (Author's calculation).

In figure 8 we see results for MDD which are also markedly different from findings obtained with stocks and REITs. Investors who stayed in the market during periods when GSCI was in downtrend not necessarily experienced deeper drawdowns. Results show that using 14 or 17-20 month SMA and holding GSCI position during downtrending market for more than 13 months MDD actually would be even lower than in uptrend. Statistical significance for the difference of means in this area is also robust (p - value < 0.05).

4.5. Summary of analysis results

After examining each asset class separately in this section we will summarize our results. Analysis showed that using simple SMA rule for trend determination could be impressively usefull when applied to investing in REITs. For investors participating in US or EAFE stocks risk could also be significantly reduced. This is correct for both our tested risk measures – standard deviation (SD) and maximum drawdown (MDD). However results with S&P GSCI TR index differed from stocks and REITs because during downtrends (when compared to situations in uptrends) risk on average was not reduced. Pooled results are shown in Table 1.

Table 1. Difference of means in SD and MDD during uptrends and downtrends (determined by SMA method) of asset classes (Author's calculation)

	Standard deviation (SD), monthly		**Maximum drawdown (MDD)**	
	downtrend vs uptrend	p-value	downtrend vs uptrend	p-value
US stocks	1.04 %	0.001	-4.88 %	0.001
EAFE stocks	1.04 %	0.001	-3.77 %	0.007
REITs	2.26 %	0.003	-7.60 %	0.004
GSCI	-0.53 %	0.142	0.72 %	0.387

From table 1 we see that If SMA method was applied to US and EAFE stocks during our testing period, avoiding of downtrending market could lead to 4.88 % and 3.77 % smaller average drawdowns (MDD) respectively and monthly volatility could be reduced by about 1.04 %. Best results could be achieved with REITs because here by simply avoiding downtrends investors could lower their average MDD by 7.6 % and volatility could be reduced by 2.26 %. These results are statistically significant because calculated p-values are much lower than 0.01.

However results obtained from commodity (GSCI) analysis are not as satisfying because in this case findings lack statistical significance.

This separation and different outcomes between stocks/REITs vs commodities might be explained by different fundamental factors such as seasonality which drive commodity prices. But this notion needs further investigation.

5. Conclusions

As recent crisis revealed, diversification does not always work flawlessly. When turbulent markets distort long term correlations between asset classes, investors' portfolios are put to greater than expected risk.

Studies show that in periods when market conditions are strongly deviated from historical norms investors tend to act irrationally. Thus, sistematic irrationality reduction could be very beneficial to both retail and professional investors.

While standard deviation is one of the main risk measures used by academia, in this article we argue that maximum drawdown is more relevant if interpreted from behavioural finance viewpoint and should be also considered seriously. Consequently, in this paper as a risk measure maximum drawdown was used in tandem with standard deviation.

Investigation presented in this article thoroughly explores concept of simple moving averages (SMA) which is one of the most popular technical analysis (TA) disciplines.

Unlike most studies about moving averages, in this paper SMA concept is examined particularly in the role of risk management. Also, in this article beside stocks several other less researched asset classes are added to the analysis.

In order to evaluate if risk can be reduced by using SMA method historical data series of chosen asset classes using various lengths of SMA were separated into periods of downtrend and uptrend. Then averages of standard devation and maximum drawdown were calculated for various holding periods in downtrending and uptrending market conditions. Lastly, differences of these averages between downtrend and uptrend were calculated and their significance was evaluated.

Results of this study reveal that SMA method when used as a trend indicator for main stock and REIT indices can significantly reduce standard deviation and maximum drawdown measures. Findings suggest that longer term (9-20 months) simple moving averages yielded best results for those asset classes. However findings obtained from GSCI analysis are not as satisfactory because in this case results lack statistical significance.

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