This is the post print version of the article, which has been published in Risk management. 2018, 20 (3), 258-272. http://dx.doi.org/10.1057/s41283-018-0036-1

Risk and Return of a Trend Chasing Application in Financial Markets: An Empirical Test

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Abstract

The paper introduces an application of the moving average trend-chasing rule that effectively reduces the risk of portfolios. The results are fairly robust: all our moving average lags produce about 36% (34%) less Value-at-Risk and about 31% (30%) less Expected Shortfall without giving up any returns on average after transaction costs compared to the buy-and-hold strategy, calculated in local currencies (in U.S. dollars). In addition, the paper finds that the volatility of returns follows a similar pattern by producing on average 29% (30%) less volatility in local currencies (in U.S. dollars). Moreover, the CAPM betas of the trading rule are significantly lower (50%) than in the buy-and-hold strategy.

Keywords: Value-at-Risk, Expected Shortfall, Volatility, Investment Decision, Stock Returns

JEL Classification: G02, G11, G32

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Introduction

Can we reduce the risk of portfolios without giving up returns by utilizing a simple moving average trading rule in the global financial market? The paper provides a positive answer to this critical question. Risk professionals utilize mainly two measures to evaluate the risk of financial portfolios, namely the Value-at-Risk (VaR), and the Expected Shortfall (ES) (see, for example Diaz *et al.*, 2017).

Yamai and Yoshiba (2005) note that, while VaR is in standard use among professionals, it has a couple of shortcomings. First, it ignores any losses beyond the VaR level. ES measures also this so-called tail risk (Artzner *et al.*, 1999), which is essential in stock markets, where returns are not necessarily normally distributed. Starting from Nelson (1991), the consent has been that stock market return distributions are asymmetric with high kurtosis and a fat negative tail. However, even ES may err in measuring the tail risk when high (low) market turbulence is followed by low (high) turbulence (Yamai and Yoshiba). Another shortcoming of VaR is that it is not a coherent risk measure. Acerbi and Tasche (2002) prove that ES is a natural coherent alternative. Yamai and Yoshiba conclude that risk managers should utilize both VaR and ES to derive reliable risk measures.

In this paper, we follow Yamai and Yoshiba (2005) by reporting both VaR and ES measures from January 1, 1987 to April 30, 2016. We utilize the non-parametric historical simulation technique of Cabedo and Moya (2003), assuming that the extensive data set compensates asymmetric bull and bear market effects in return distributions.

We find that all our trading rules produces on average 36% (34%) less VaR at 95% confidence level without giving up any returns after transaction costs compared to the buy-and-hold strategy, calculated in local currencies (in U.S. dollars). In addition, we report similar results with the ES measures: all our moving average lags provide about 31% (30%) less expected negative returns beyond VaR levels at 95% confidence level. An interesting finding is that we get almost identical results in the reduction of volatility: all the trading rules produce about 29% (30%) less volatility compared to the buy-and-hold strategy, calculated in local currencies (in U.S. dollars).

The paper introduces an application of Gartley's (1935) trend-chasing moving average rule, where monthly closing prices are used instead of daily observations. For example, assuming that a 10-month period is an approximation for 200 trading days, we construct a moving average with 10 observations. Consequently, we have moving average (MA) rules with 9, 8, 7, 6, 5, 4, 3, and 2 observations. The simple trading rule is the following: When the trend-chasing moving average turns higher (lower) than the current monthly closing price, we invest to the risk-free (risky) asset in the next trading day. Thus, the trading rule provides a market timing strategy.

The data covers nearly 30 years (from January 1, 1987 to April 30, 2016) resulting in 166446 observations of daily returns with dividends included. The data are from MSCI-world index, including 23 developed countries. We calculate the results both in local currencies and in U.S. dollars. In local currencies, the annualized average return is about +8.8% *after* transaction costs, while the respective finding with the buy-and-hold strategy is +7.3%. In U.S. dollars, the moving average rule produces about +7.8% annualized average return after transaction costs, while the buy-and-hold strategy produces +7.5% returns.

The empirical literature on moving average trading rules is extensive. In their seminal paper, Brock *et al.* (1992) test different versions of moving average based trading rules in U.S. stock markets between January 1897 and December 1986. They conclude that all trading rules produce statistically significant profits against the benchmark (holding cash) before the trading rule costs. Sullivan *et al.* (1999) extend the time span to cover years 1987–1996 and allow for short selling. They find that, after trading costs, no moving average rule outperforms the market. Allen and Karjalainen (1999) use a genetic algorithm to develop the best ex-ante model, and use the S&P500 data between January 1926 and December 1995. They find some evidence of outperforming the buy-and-hold strategy. Lo et al. (2000) find that risk averse investors benefit from technical trading rules, mainly because they reduce volatility of the portfolio without giving up returns when compared to the buy-and-hold strategy.

Estimated with CAPM, we find economically and statistically significant abnormal returns after transaction costs. The annualized average alpha is 0.033 (0.023) in local currencies (U.S. dollars) with the nine moving average rules. Furthermore, the average CAPM beta is 0.49 (0.51) in local currencies (U.S. dollars). The lower beta value comes from the fact that the trading strategy does not always expose investor to the stock market, but it advices the timing, which results in the positive average alpha. This suggests that the moving average rule, as a part of the asset allocation rule, reduces the beta exposures of investment compared to the buy-and-hold strategy without giving up returns on average.

Moreover, Han *et al.* (2013) report that moving average trading rule outperforms (after transaction costs), when the portfolio is sorted by recent volatility of returns. Their data contain U.S. stock markets from January 1973 to December 2008. They suggest that higher volatility produces higher abnormal returns thus yielding trend-chasing profits. Our result is consistent with the findings of Han *et al.* that higher volatility predicts higher trend chasing returns for the next period. This is to say that when stock market returns are volatile, some other signal can be false and then investors rely on technical analysis more when compared to the low volatile periods. In addition, Moskowitz *et al.* (2011) find positive autocorrelation in returns up to 12 months, which suggests that the time series momentum contributes to trend-chasing profits. We find that lagged excess market returns explain statistically significantly our moving average trend-chasing returns up to the fourth lag (with some variability). The predictive effect of market excess returns on our trend chasing rule can be explained by the time-varying risk premia (Cochrane 2008).

In addition, for example, Campbell and Yogo (2006), Ang and Bekaert (2007), Campbell and Thompson (2008), Hjalmarsson (2010) and Maio (2014) report that stock markets returns are forecastable mainly by short-term interest rates over a short horizon. Our finding that the change in the local risk-free rate predicts the trend-chasing returns negatively for the next month is in line with their results.

Moreover, we find that the existing volatility of daily market returns has a statistically significant negative effect on the existing trend-chasing returns. The results are robust, because they occur with all lags, both in local currencies and in U.S. dollars. This deserves some discussion. Ang *et al.* (2006, 2009) report that low (high) volatility in market returns suggests high (low) market returns, which is an anomaly against the mean-variance paradigm. Baker *et al.* (2011) argue that this phenomenon is caused by investors' irrational preferences for high volatility. Our trend chasing rule advices to invest either in the stock market or in the risk-free rate. Hence, if the trend-chasing rule performs better than the buy-and-hold strategy, it would advise to be out of (in) the stock market, when there is a downward (upward) trend in the market. Then, the negative effect of the existing market volatility on trend chasing returns suggests that the rule observes a connection of high volatility and low market returns in the spirit of Ang *et al.* and Baker *et al.*

Empirical test

In the empirical test, we use a simple application of the trend-chasing rule of Gartley (1935). Thus, our core trading rule is defined as follows:

Definition 1: We invest either all wealth to the stock market index or to the risk-free asset, whereas the moving average rule advices the timing.

Our benchmark is the buy-and-hold strategy, which is a standard benchmark in trading rule tests in the literature.

Definition 2: Our benchmark is the buy-and-hold strategy.

The collection of the information of past prices is assumed costless and, following Allen and Karjalainen (1999) and Han *et al.* (2013), the transaction costs are fixed to 0.25% per transaction. In addition, we follow the literature by ignoring personal taxes. The trend chasing trading rule to buy or sell in the first day of next month is

$$\begin{aligned} & P_{t-1} > \left[\frac{P_{t-1} + P_{t-2} + \dots + P_{t-\tau}}{\tau} \right] \rightarrow buy \\ & and \\ & P_{t-1} < \left[\frac{P_{t-1} + P_{t-2} + \dots + P_{t-\tau}}{\tau} \right] \rightarrow sell \end{aligned} \qquad (1)$$

where τ is the size of the fixed window (in monthly observations). In the test, we use nine values for τ. This is based on the following construction: We presume that using monthly data instead of daily data reduces the effect of false signals due to the volatility of daily prices, assuming that a 10-month period is an approximation for 200 trading days. Hence, we construct a moving average (MA) with 10 observations. In addition, we have a 9-month window for 180 days, an 8-month window for 160 days, a 7-month window for 140 days, a 6-month window for 120 days, a 5-month window for 100 days, a 4-month window for 80 days, a 3-month window for 60 days, and a 2-month window for 40 trading days.

We use a simple crossover rule. For example, when the actual closing price has been higher (lower) than the moving average price and it turns lower (higher) than the moving average price, it is a signal to close the current position in the first day of the next month, and to invest to the one-month risk-free rate (stock markets).

Thus, during the testing period, (from January 1, 1987 to April 30, 2016) we have either a long position for the MSCI indices, or we put the assets into the one-month ECU deposit rate (from January 1987 to December 1998, source: ec.europe.eu/eurostat), and one-month euribor rate (from January 1999 to April 2016, source: ec.europe.eu/eurostat). We use one-month Euribor rate in this study, because we target at European investors. Note that the results are similar when the one-month U.S. treasury bill is taken as the risk-free rate.[1]

The Data

We use global daily data from January 1, 1987 to April 30, 2016, Then, for example, observations from March 1986 to December 1986 are the first 10 ones that determine the trading rule position. The convenient source for such market data is the MSCI World Index (source: www.msci.com). The MSCI indices are free float-adjusted market capitalization weighted indices. At the present time, the MSCI World contains stock market series from 23 developed countries: Australia, Austria, Belgium, Canada, Finland, France, Denmark, Germany, Holland, Hong Kong, Ireland, Israel, Italy, Japan, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the UK, and the USA. We include all the above countries' indices in the calculations using total return indices where dividends are included. That is, we have a comprehensive sample over nearly 30 years from the global developed stock markets.

We utilize data both in local currencies and in U.S. dollars. Unfortunately, the MSCI-Israel data are not available for the period from January 1, 1987 to December 31, 1992. For the similar reason, the test samples of MSCI-Finland, MSCI-Ireland, MSCI-New Zealand and MSCI-Portugal start from November 1, 1988. Table (1) shows the descriptive statistics for the returns of these 23 indices as a summary of the buy-and-hold strategy statistics calculated in annualized monthly log returns with dividends included.

Table (1) about here.

Table (1) shows that the annualized average MSCI-country returns vary from +0.007 to +0.123 with the average +0.073 in local currencies. The annualized monthly standard deviations range from 0.153 to 0.303 with the average 0.207. In addition, skewness (kurtosis) ranges from -3.794 to -0.013 (3.473 to 41.395) with the average -0.950 (7.984). According to the Jarque-Bera tests, none of the returns are normally distributed. We utilize historical simulation (Cabedo and Moya, 2003) when calculating VaR and ES. We define VaR as possible maximum loss over next month within 95% confidence level, and ES as the average loss when the loss exceeds the VaR level. Table (1) shows that VaR ranges from -5.9% to -11.4% with the average -8.7% in the current wealth level, and ES ranges from -10.1% to -18.5% with the average -13.6% in the current wealth level. Note that VaR and ES are transformed from the log returns to the simple returns.

Table (2) about here.

Table (2) shows that the annualized average MSCI-country returns vary from +0.021 to +0.128 with the average +0.075 in U.S. dollars. The annualized monthly standard deviations range from 0.173 to 0.312 with the average 0.228. In addition, skewness (kurtosis) ranges from -2.257 to 0.026 (3.486 to 19.179) with the average -0.845 (6.777). According to the Jarque-Bera tests, none of the returns are normally distributed. Moreover, VaR ranges from -6.9% to -13.5% with the average -9.6% in the current wealth level, and ES ranges from -10.2% to -18.9% with the average -14.8% in the current wealth level.

Table (3) shows the performance of the buy-and-hold strategy and our trend-chasing rule with nine different lags in local currencies.[2]

Table (3) about here.

Table (3) reports that the average annualized monthly returns (7926 monthly observations) for the trend-chasing rule after transaction costs is +0.088 in local currencies and +0.073 for the buy-and-hold strategy. The annualized volatility of monthly returns is much lower for the MA rule than for the buy-and-hold strategy, namely 0.148 compared to 0.207 in local currencies. VaR is reduced by 35.7% on average in current wealth, and ES is reduced 30.5% on average compared to the buy-and-hold strategy measures. This suggests that the market timing produced by the MA rule for asset allocation has reduced the risk of investment in global stock markets during the last 30 years. The results are robust, because all moving average lags produce consistent results. For the market specific results, Figure (1) shows the performance of the trading rules in all versions (MA 10 – MA 2) in German stock markets from January

1987 to December 1998 in Deutsche Mark, and in Euro currency from the beginning of 1999.

Figure (1) about here.

Figure (1) illustrates that the MA lags (except MA2, MA3 and MA4) beat the buy-and-hold cumulative returns in the sample. There seems to be sluggish stochastic trends in price series after year 2000, since the MA10, MA9, MA8, MA7, MA6 and MA5 lags outperform the buy-and-hold cumulative returns. Thus, it seems that MA10-MA5 lags capture the temporary negative trends, that last long enough to be worth to stay out of the stock markets from the year 2000.

Table (4) reveals that the German stock market positions according to the trading rules range from 59% (MA2) to 68% (MA7), where the reduction of risk is fairly stable in all MA lags.

Table (4) about here.

Table (5) shows the performance of our trend-chasing rule with nine different lags in U.S. dollars.[3]

Table (5) about here.

Table (5) reports that the average annualized monthly return (7926 monthly observations) for the trend-chasing rule after transaction costs is +0.078 in U.S. dollars and +0.075 for the buy-and-hold strategy. The annualized volatility of monthly returns is much lower for the trend-chasing rule than for the buy-and-hold strategy, namely 0.160 compared to 0.228 in local currencies. The trading rule reduces VaR by 33.8% (in current wealth) on average and ES by 30.0% on average compared to the buy-and-hold strategy. This suggests that the market timing produced by the MA rule with asset allocation has reduced the risk of investment in global stock markets during the last 30 years. The results are robust, because all MA lags produce consistent results.

Empirical estimations

CAPM estimations

We apply the capital asset pricing model by Sharpe (1964) with constant α (Jensen, 1967) and conduct pooled panel data (times series and cross-sectional dimensions) OLS regressions where the excess returns of the trend chasing moving average rule is explained by MSCI-world excess returns. The equation reads

$$R_{it} - r_{ft} = \alpha + \beta(r\ world_t - r_{ft}) + e_{it} \qquad (2)$$

where parameter α presents abnormal returns over the market return (if it is positive and statistically significant) and the risk parameter β describes zero cost portfolio returns on the market factor (MSCI-world). Moreover, R_{it} is the moving average trend chasing return, r_{ft} is one-month euribor, and $r\ world_t$ is the MSCI-world return. We estimate Equation (2) in local currencies and in U.S. dollars in nine moving average lags (10, 9, 8, 7, 6, 5, 4, 3 and 2) with 7926 monthly observations in all estimations. Table (6) reports the results with robust standard errors.

Table (6) about here.

From Table (6) we observe that the average β becomes +0.49 (+0.51) in local currencies (in U.S. dollars) suggesting that the trend-chasing moving average rule reduces the beta exposures of investment, because the β of the buy-and-hold strategy is approximately one. In addition, the average annualized α becomes +0.033 (+0.023) in local currencies (in U.S. dollars) where all MSCI-country α*: s* is statistically significant.

Predictive explanatory estimations

Next we conduct predictive fixed effect panel data regressions (FEPD), where the trend-chasing moving average rule excess return $R_{it} - r_{ft}$ is explained by the previous month's change in local three month interest rate Δr_{it-1}, the annualized previous month's *daily* volatility of market returns v_{it-1} (to capture the predictive power of volatility by Han *et al.*, 2013), and the previous five month MSCI-country excess returns $m_{t-1},\ldots m_{t-5}$ (to capture time series momentum effect, as suggested by Moskowitz et al., 2011)[4]. Recall that our trend chasing strategy means investing either in the market index or in the risk-free rate. In addition, we include the annualized current month's daily volatility of market returns v_{it} as an explanatory variable to capture the effect of existing volatility on the trend chasing excess returns. We use the changes in local risk-free rates as a predictive explanatory variable, assuming that the local three-month interest rate serves as a proxy for the local risk-free rate (source: http://stats.oecd.org). We use changes, because risk-free rate levels have unit roots, but all change series are stationary according to the unit root tests. Thus, the FEPD estimation follows

$$R_{it} - r_{ft} = \beta_{i1} + \beta_2 \Delta r_{it-1} + \beta_3 v_{it-1} + \beta_4 v_{it} + \beta_5 m_{it-1} + \ldots + \beta_9 m_{it-5} + e_{it} \quad (3)$$

We estimate Equation (3) with the moving average lags 10, 9, 8, 7, 6, 5, 4, 3 and 2 in local currencies and in U.S. dollars. The results from the FEPD regressions are in Table (7). We report the results for the variables only when they are statistically significant at 5% level (two-sided test) and we use robust standard errors in the estimations.

Table (7) about here.

Table (7) shows that the previous change of local risk-free rate forecasts statistically significantly the trend-chasing returns in local currencies, but not in U.S. dollars (except for the moving average lag 5). Positive changes make the trend-chasing returns fall in the next period. The previous month's volatility of daily market returns forecasts statistically significantly the trend-chasing returns so that when the volatility is rising, the trend chasing returns also rise in the next month. These results are robust in local currencies and in U.S. dollars and are consistent with the findings of Han *et al.* (2013). However, according to our results, the present volatility of daily market returns has negative effect on the present trend-chasing returns.

Recall that our long position is identical to market returns. Table (7) reports that the time series momentum on market excess returns has a statistically significant positive effect on the trend chasing excess returns, but only with the first, second and third lags in local currencies. In U.S. dollars, the first and third lags are positive, while the fourth turns negative in correlation.

Conclusions

The paper introduces a simple application of the moving average market timing rule, where we invest either in the stock market index or in the risk-free rate. Our findings over the last 30 years in global developed stock markets are important to the risk management professionals, because the rule clearly reduces risk for an investor after transaction costs without giving up any returns on average. It reduces Value-at-Risk of the wealth level about 36% (34%) compared to the buy-and-hold strategy performance in local currencies (in U.S. dollars), where VaR is calculated in the standard 95% confidence level. Moreover, the trading rule decreases Expected Shortfall 31% (30%) on average in local currencies (in U.S. dollars) compared to the buy-and-hold performance.

In addition, even though the market timing returns are not normally distributed, the annualized volatility of the trading rule portfolio is about 29% less than the market in local currencies (30% in U.S. dollars). We can speculate that the slightly lower performance with lags from 4 to 2 is due to growing transaction costs since these rules advice more transactions compared to the lags 10 to 5. Note that the risk and return differences are marginal with lags from 10 to 5. The data includes all developed MSCI-country indices (with dividends included) from January 1, 1987 to April 30 2016 resulting to 7926 monthly returns in total. Our idea is to avoid possible false signals on daily prices by utilizing monthly closing prices when calculating the moving averages.

The results support the theoretical results of Zhu and Zhou (2009), and the empirical results of Lo *et al*. (2000) that trend-chasing as a part of asset allocation adds value for a risk averse investor. In addition, our results are consistent with the predictive power of volatility found by Han *et al.*, (2013), and the time series momentum effect found by Moskowitz *et al.* (2011). Moreover, our results support the findings of Maio (2014) and others as the change in the local risk-free rate predicts the trend-chasing returns negatively for the next month. Finally, our results are consistent with Ang *et al.* (2006, 2009) and Baker *et al*. (2011) as we find a connection between high volatility and low market returns.

Acknowledgements: I greatly acknowledge the helpful comments of Hannu Laurila, the editor and two anonymous referees.

Conflict of Interest: The author declares that he has no conflict of interest.

End Notes

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[1] Calculations with the one-month U.S. treasury bill rate as the risk-free rate of return are available upon request.

[2] Market specific calculations are available upon request.

[3] Market specific calculations are available upon request.

[4] Note that the moving average technique uses prices, but there has to be returns in the regression analysis to restore stationarity. Thus, any straight comparisons between MA lags and return lags is useless.

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Table (1). Summary statistics of the MSCI-country indices, in local currencies.

	mean	**standard deviation**	**skewness**	**kurtosis**	**VaR**	**ES**
Australia	0.088	0.171	-3.794	41.395	-0.059	-0.103
Austria	0.038	0.243	-0.940	6.823	-0.103	-0.171
Belgium	0.083	0.196	-1.600	10.761	-0.080	-0.144
Canada	0.082	0.153	-1.236	7.898	-0.063	-0.103
Denmark	0.123	0.186	-0.506	4.086	-0.079	-0.115
Finland	0.088	0.303	-0.277	4.790	-0.114	-0.185
France	0.071	0.192	-0.583	4.389	-0.085	-0.124
Germany	0.065	0.218	-0.964	5.730	-0.096	-0.155
HK	0.107	0.272	-1.334	12.240	-0.108	-0.172
Holland	0.089	0.184	-1.167	6.002	-0.084	-0.135
Ireland	0.038	0.215	-0.757	4.664	-0.101	-0.146
Israel	0.064	0.216	-0.477	4.004	-0.104	-0.134
Italy	0.036	0.218	-0.013	3.473	-0.091	-0.123
Japan	0.007	0.198	-0.391	4.076	-0.083	-0.124
New Zealand	0.064	0.174	-0.087	4.666	-0.073	-0.101
Norway	0.086	0.238	-1.297	6.926	-0.089	-0.165
Portugal	0.034	0.203	-0.147	4.493	-0.080	-0.125
Singapore	0.061	0.240	-1.836	15.133	-0.092	-0.172
Spain	0.087	0.221	-0.718	5.083	-0.096	-0.143
Sweden	0.114	0.234	-0.401	5.119	-0.111	-0.151
Switzerland	0.078	0.167	-1.081	6.631	-0.074	-0.115
UK	0.078	0.157	-1.190	8.743	-0.070	-0.101
USA	0.096	0.154	-1.051	6.498	-0.068	-0.102
average buy and hold	**0.073**	**0.207**	**-0.950**	**7.984**	**-0.087**	**-0.136**

Notes:

We calculate average annualized returns, standard deviations, skewness, kurtosis, Value-at-Risk and Expected Shortfall in monthly observations, where dividends are included. The sample period is from January 1987 to April 2016, except for MSCI-Finland, MSCI-Ireland, MSCI-New Zealand and MSCI-Portugal the sample is from November 1988 to April 2016 and MSCI-Israel the sample is from November 1993 to April 2016. We report all statistics calculated in natural logarithmic returns. VaR and ES are transformed from the log returns to the simple returns

Table (2). Summary statistics of the MSCI-country indices, in U.S. dollars.

	mean	standard deviation	skewness	kurtosis	VaR	ES
Australia	0.093	0.238	-2.257	19.179	-0.082	-0.159
Austria	0.043	0.269	-1.094	8.249	-0.107	-0.183
Belgium	0.089	0.214	-1.836	13.722	-0.077	-0.141
Canada	0.085	0.198	-1.082	7.307	-0.079	-0.131
Denmark	0.128	0.201	-0.683	5.662	-0.087	-0.123
Finland	0.081	0.312	-0.330	4.499	-0.135	-0.189
France	0.075	0.209	-0.575	4.268	-0.100	-0.137
Germany	0.069	0.232	-0.763	4.997	-0.102	-0.161
Hong Kong	0.103	0.272	-1.317	12.124	-0.108	-0.171
Holland	0.094	0.196	-1.128	6.194	-0.090	-0.138
Ireland	0.037	0.228	-0.920	5.695	-0.092	-0.158
Israel	0.056	0.233	-0.487	3.991	-0.116	-0.147
Italy	0.029	0.244	-0.282	3.486	-0.111	-0.149
Japan	0.021	0.210	0.026	3.767	-0.086	-0.120
New Zealand	0.068	0.226	-0.373	4.173	-0.092	-0.135
Norway	0.083	0.275	-1.175	6.954	-0.103	-0.184
Portugal	0.027	0.233	-0.346	4.571	-0.094	-0.139
Singapore	0.077	0.263	-1.504	11.743	-0.109	-0.185
Spain	0.084	0.244	-0.546	4.566	-0.100	-0.156
Sweden	0.108	0.256	-0.579	4.672	-0.118	-0.166
Switzerland	0.097	0.173	-0.576	4.332	-0.084	-0.114
UK	0.078	0.175	-0.553	5.228	-0.069	-0.107
USA	0.096	0.154	-1.051	6.498	-0.068	-0.102
average buy and hold	**0.075**	**0.228**	**-0.845**	**6.777**	**-0.096**	**-0.148**

Notes:

We calculate average annualized returns, standard deviations, skewness, kurtosis, Value-at-Risk and Expected Shortfall in monthly observations, where dividends are included. The sample period is from January 1987 to April 2016, except for MSCI-Finland, MSCI-Ireland, MSCI-New Zealand and MSCI-Portugal the sample is from November 1988 to April 2016 and MSCI-Israel the sample is from November 1993 to April 2016. We report all statistics calculated in natural logarithmic returns. VaR and ES are transformed from the log returns to the simple returns.

Table (3). Summary statistics of the moving average trend-chasing rule returns (monthly moving average (MA) lags of 10, 9, 8, 7, 6, 5, 4, 3, 2) after transaction costs in local currencies.

	mean	**standard deviation**	**skewness**	**kurtosis**	**VaR**	**ES**
average MA10	0.088	0.149	-1.060	13.824	-0.058	-0.096
average MA9	0.089	0.148	-1.033	14.125	-0.057	-0.094
average MA 8	0.092	0.148	-1.023	14.228	-0.056	-0.094
average MA 7	0.092	0.147	-1.001	14.211	-0.051	-0.094
average MA 6	0.092	0.147	-0.948	14.270	-0.056	-0.094
average MA 5	0.091	0.148	-0.952	14.245	-0.057	-0.093
average MA 4	0.084	0.147	-0.855	13.810	-0.057	-0.094
average MA 3	0.084	0.146	-0.718	12.745	-0.055	-0.092
average MA 2	0.077	0.148	-0.854	13.081	-0.057	-0.097
average MA	**0.088**	**0.148**	**-0.938**	**13.838**	**-0.056**	**-0.094**
average buy and hold	0.073	0.207	-0.950	7.984	-0.087	-0.136
difference in %	**20.5**	**-28.5**	**-1.2**	**73.3**	**-35.7**	**-30.5**

Notes:

We calculate average annualized returns, standard deviations, skewness, kurtosis, Value-at-Risk and Expected Shortfall in monthly observations, where dividends are included. The sample period is from January 1987 to April 2016, except for MSCI-Finland, MSCI-Ireland, MSCI-New Zealand and MSCI-Portugal the sample is from November 1988 to April 2016 and MSCI-Israel the sample is from November 1993 to April 2016. We report all statistics calculated in natural logarithmic returns. VaR and ES are transformed from the log returns to the simple returns. Please, note that we invest either to the stock market index or to the risk-free asset, whereas the MA rule advices the timing.

Table (4). Summary statistics of the moving average trend-chasing rule MSCI-Germany returns (monthly moving average (MA) lags of 10, 9, 8, 7, 6, 5, 4, 3, 2) after transaction costs in local currencies.

	mean	**standard deviation**	**skewness**	**kurtosis**	**VaR**	**ES**	**long positions**
Germany 10	0.091	0.159	-1.256	9.587	-0.058	-0.113	0.665
Germany 9	0.083	0.157	-1.218	9.464	-0.057	-0.113	0.662
Germany 8	0.096	0.153	-1.045	8.951	-0.055	-0.106	0.670
Germany 7	0.086	0.155	-1.036	8.650	-0.060	-0.109	0.676
Germany 6	0.082	0.152	-1.071	9.142	-0.057	-0.108	0.653
Germany 5	0.077	0.153	-1.057	8.980	-0.060	-0.109	0.651
Germany 4	0.053	0.154	-1.085	8.884	-0.065	-0.113	0.634
Germany 3	0.058	0.142	-0.676	7.460	-0.055	-0.100	0.611
Germany 2	0.063	0.149	-1.345	11.995	-0.057	-0.112	0.585
buy and hold	0.065	0.218	-0.964	5.730	-0.096	-0.155	1.000

Notes:

We calculate average annualized returns, standard deviations, skewness, kurtosis, Value-at-Risk, Expected Shortfall and the portion of long positions in monthly observations, where dividends are included. The sample period is from January 1987 to April 2016. We report all statistics calculated in natural logarithmic returns. VaR and ES are transformed from the log returns to the simple returns. Note that we invest either to the stock market index or to the risk-free asset, whereas the MA rule advices the timing.

Table (5). Summary statistics of the moving average trend-chasing rule returns (monthly moving average (MA) lags of 10, 9, 8, 7, 6, 5, 4, 3, 2) after transaction costs in U.S. dollars.

	mean	**standard deviation**	**skewness**	**kurtosis**	**VaR**	**ES**
average MA 10	0.083	0.160	-0.817	10.917	-0.063	-0.104
average MA9	0.083	0.162	-0.772	10.865	-0.063	-0.104
average MA 8	0.082	0.161	-0.758	10.816	-0.064	-0.105
average MA 7	0.080	0.161	-0.698	10.657	-0.064	-0.104
average MA 6	0.079	0.161	-0.704	10.905	-0.064	-0.105
average MA 5	0.076	0.160	-0.685	11.204	-0.063	-0.102
average MA 4	0.076	0.158	-0.632	11.085	-0.063	-0.101
average MA 3	0.077	0.157	-0.429	9.901	-0.063	-0.099
average MA 2	0.072	0.158	-0.626	10.521	-0.063	-0.104
average MA	**0.078**	**0.160**	**-0.680**	**10.763**	**-0.064**	**-0.103**
average buy and hold	0.075	0.228	-0.845	6.777	-0.096	-0.148
difference in %	**4.8**	**-29.8**	**-19.5**	**58.8**	**-33.8**	**-30.0**

Notes:

We calculate average annualized returns, standard deviations, skewness, kurtosis, Value-at-Risk and Expected Shortfall in monthly observations, where dividends are included. The sample period is from January 1987 to April 2016, except for MSCI-Finland, MSCI-Ireland, MSCI-New Zealand and MSCI-Portugal the sample is from November 1988 to April 2016 and MSCI-Israel the sample is from November 1993 to April 2016. We report all statistics calculated in natural logarithmic returns. VaR and ES are transformed from the log returns to the simple returns. Note that we invest either to the stock market index or to the risk-free asset, whereas the MA rule advices the timing.

Table (6). Results of the CAPM moving average trend chasing rule returns (monthly moving average lags of 10, 9, 8, 7, 6, 5, 4, 3, 2) after transaction costs, in local currencies and in U.S. dollars.

	α of returns	**t-value of α**	**β of returns**	**t-value of β**
MA 2	0.022	4.17	0.491	24.9
MA 3	0.030	6.04	0.456	23.2
MA 4	0.029	5.43	0.483	21.8
MA 5	0.037	7.03	0.497	22.6
MA 6	0.038	7.72	0.491	22.6
MA 7	0.037	7.79	0.490	23.6
MA 8	0.038	8.29	0.495	23.5
MA 9	0.034	6.77	0.495	22.9
MA 10	0.033	6.46	0.503	23.1
total average	0.033	6.63	0.489	23.1
buy and hold	0.000	0.45	1.015	30.1
MA 2, $	0.017	3.25	0.492	22.9
MA 3, $	0.027	4.34	0.473	22.8
MA 4, $	0.021	6.46	0.491	22.1
MA 5, $	0.020	4.17	0.515	26.6
MA 6, $	0.023	5.32	0.519	24.7
MA 7, $	0.024	5.75	0.52	24.7
MA 8, $	0.025	5.7	0.519	23.1
MA 9, $	0.027	5.88	0.512	22.4
MA 10, $	0.027	6.28	0.514	22.1
total average, $	0.023	5.24	0.506	23.5
buy and hold, $	0.000	0.69	1.093	32.7

Notes:

We utilize pooled panel data OLS regression (R_{it} - r_{ft} = $\alpha + \beta(r\ world_t - r_{ft}) + e_{it}$), with times series and cross-sectional dimensions, where R_{it} is the moving average trend chasing return, r_{ft} is one-month euribor, $r\ world_t$ is MSCI-world return. The sample period is from January 1987 to April 2016. We report all statistics calculated in natural logarithmic returns after transaction costs, where above is the results in local currencies and then in U.S. dollars. Total sample size is 7926 observations in all estimations.

Table (7). The FEPD estimation results.

	first lag difference of local risk-free rate	first lag annualized of daily volatility	present annualized of daily volatility	first lag of excess market returns	second lag of excess market returns	third lag of excess market returns	fourth lag of excess market returns	fifth lag of excess market returns
MA 2	-0.002	0.087	-0.131	0.050	-0.020	0.034	-0.030	
MA 3	-0.002	0.082	-0.129	0.032		0.034		
MA 4	-0.002	0.091	-0.148	0.033		0.027		
MA 5	-0.002	0.098	-0.155	0.031	0.020	0.022		
MA 6	-0.002	0.090	-0.158		0.018			
MA 7	-0.002	0.092	-0.161		0.019			
MA 8	-0.002	0.094	-0.167		0.019			
MA 9	-0.002	0.095	-0.168		0.020			
MA 10	-0.001	0.099	-0.177		0.016	0.019		
total average	**-0.002**	**0.092**	**-0.155**	**0.037**	**0.013**	**0.027**	**0**	**0**
buy and hold	**-0.003**	**0.175**	**-0.320**	**0.079**	**-0.041**	**0.041**	**-0.031**	**0**
MA2 $		0.092	-0.134	0.037		0.029	-0.020	
MA 3 $		0.085	-0.125	0.030		0.030		
MA 4 $		0.090	-0.146	0.027		0.015	-0.019	
MA 5 $	-0.001	0.097	-0.157	0.027			-0.017	
MA 6 $		0.100	-0.166	0.022			-0.016	
MA 7 $		0.100	-0.169	0.016			-0.020	
MA 8 $		0.100	-0.173				-0.023	
MA 9 $		0.100	-0.176			0.019	-0.021	
MA 10 $		0.100	-0.182			0.020	-0.024	
total average $	**0**	**0.096**	**-0.159**	**0.027**	**0**	**0.026**	**-0.020**	**0**
buy and hold $	**-0.003**	**0.186**	**-0.354**	**0.049**	**-0.070**	**0.063**	**-0.026**	**0**

Notes:

The estimation follows $R_{it} - r_{ft} = \beta_{i1} + \beta_2 \Delta r_{it-1} + \beta_3 v_{it-1} + \beta_4 v_{it} + \beta_5 m_{it-1} + \ldots + \beta_9 m_{it-5} + e_{it}$ where the excess returns of the trend chasing moving average rule returns R_{it} is explained by the previous month's change of local risk-free rate Δr_{it-1}, the annualized previous month's volatility of market returns v_{it-1}, the current volatility of market returns v_{it} and the previous five month of MSCI-country excess returns $m_{t-1}, \ldots m_{t-5}$. The moving average trend-chasing rule returns are monthly moving lags of 10, 9, 8, 7, 6, 5, 4, 3, 2. We report all statistics calculated in natural logarithmic returns with robust standard errors used. Note that we report the results for the variables only when they are statistically significant at 5% level (two-sided test).

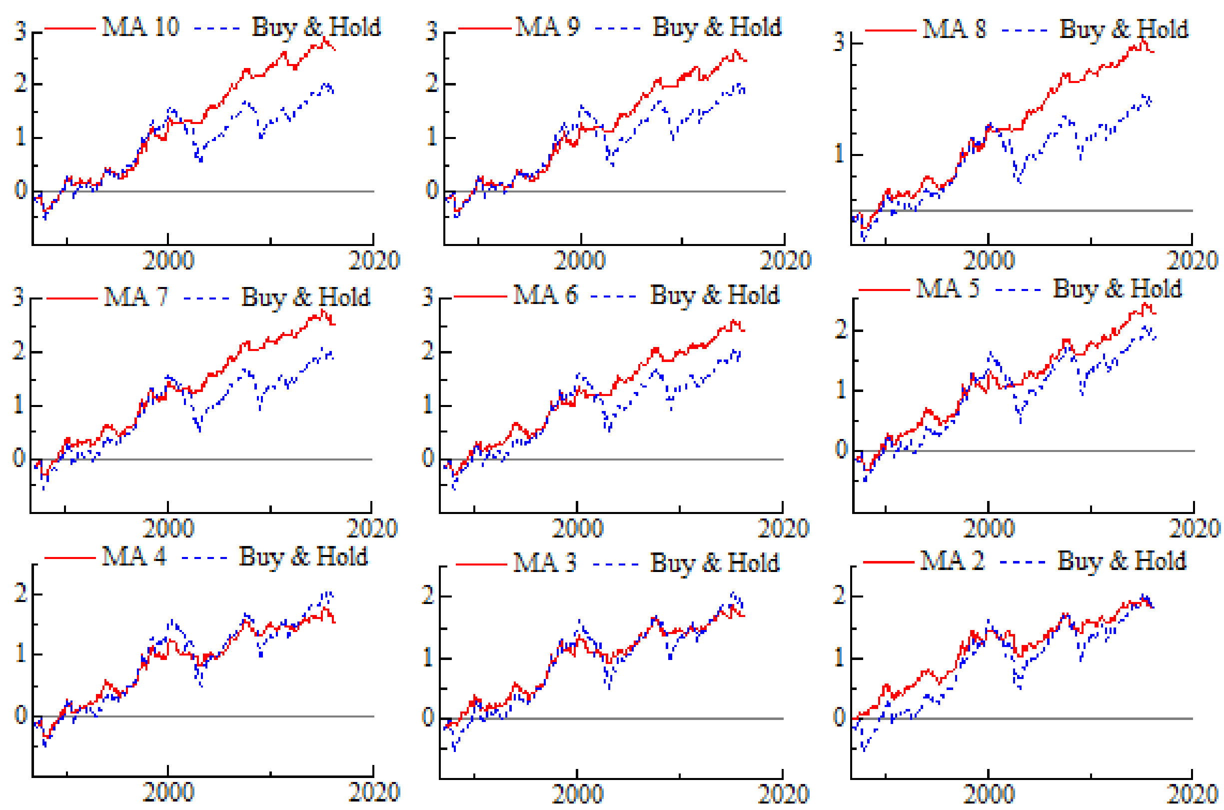

Figure (1). The cumulative returns of the trading rules (MA 10 – MA 2) compared to the cumulative buy-and-hold returns in MSCI-Germany from January 1987 to December 1998 in Deutsche Mark, and in Euro currency from January1999 to April 2016.