Risk-Adjusted Returns and Loss Avoidance in Technical Trading Rules*

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Abstract

We show that moving average and time series-based momentum trading rules reduce the occurrence of extreme losses in equity investments without compromising expected returns. The percentage of extreme negative returns avoided by following these simple strategies is higher during economic recessions. Our findings are robust to changes in specifications and are present in most national equity indices. They also survive a reality check bootstrap test for data-snooping.

Keywords: Technical trading rules, return predictability, momentum.

JEL Classification: G11, G12

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1 Introduction

Technical trading rules (TTR), or simple technical analysis methods based on momentum, are commonly used by active traders.[1] Numerous researchers have addressed the potential profitability of technical trading strategies. Some of the more prominent papers on the issue are Jegadeesh and Titman (1993), who are one of the first to document cross-sectional momentum, and Moskowitz et al. (2012), who have established a time-series momentum effect. Other papers that establish technical trading rules superiority over a buy-and-hold (BH) strategy are Brock et al. (1992), Pesaran and Timmermann (1995), Ang and Bekaert (2007), Ni et al. (2015), Marshall et al. (2017), to name but a few.

Whether technical trading strategies are indeed superior is still a matter of debate. Bollerslev and Hodrick (1992) claim that the performance of TTR is due to time varying risk premia rather than risk-adjusted outperformance. Fama and French (1992) similarly claim that TTR outperform the market by compensating for additional risk factors. Park and Irwin (2007) conduct a survey of 95 studies on technical trading rules. They report 56 studies documenting positive TTR profits, 20 with negative profits, and 19 with mixed findings. Some more recent studies questioning the TTR effectiveness are Fang et al. (2014), who document no out-performance of technical trading strategies from 1987 to 2011, and Taylor (2014), who reports that TTR profits are confined to particular episodes in mid-1960s to mid-1980s.

[1] Menkhoff (2010) conducts a survey of 692 fund managers in five countries and documents that the vast majority of them rely on technical analysis.

In analyzing the performance of a technical trading strategy (or any other strategy for that matter), academic literature tends to focus on means and standard deviations of returns. Extreme tail events are usually not explicitly analyzed, even though they carry the biggest punch. Importance of left tail risk has been brought into the spotlight by the most recent Global Financial Crisis. Therefore, it is logical to evaluate trading strategy performance based on its left tail, especially during times of distress.

We contribute to the literature by explicitly analysing left tail risk of technical trading rules. Using Dow Jones Industrial Average over 1897-2018, we show that TTR strategies not only reduce tail risk (as measured by Value-at-Risk and Expected Shortfall), but also increase risk-adjusted returns compared to a BH strategy. Moreover, an investor following a simple TTR strategy is able to avoid a high percentage of extreme negative events. Interestingly, the percentage of avoided negative events increases substantially during recessions.

Our results are robust to alternative strategy specifications and samples, as we test the TTR strategies for 39 international indices. With few exceptions, they remain robust when accounting for transaction costs. We also subject our findings to two types of bootstrap testing. First, to test the significance of the outperformance of the TTR strategies over the BH strategy we use the framework by Sullivan et al. (1999). They use a bootstrap to evaluate the expected returns and Sharpe ratios of the TTR against BH strategy. Their standard framework functions well for metrics that focus on the whole distribution, but less so for tail risk measures like Value-at-Risk and Expected Shortfall. One could argue that the best way to reduce tail risk is to invest in a risk-free rate. Thus, a BH strategy may not be the appropriate benchmark for assessing TTR performance. Therefore, in case of the tail risk measures we adjust their framework by adding an equal amount of sell signals, at random moments in time, to the BH Strategy. For example, if a TTR strategy calls for staying out of the market for 20% of the time, then 20% of return observations are randomly replaced with a risk-free rate. Our results remain robust. Our second test is the reality check bootstrap as implemented in Sullivan et al. (1999). The successful performance of any given strategy could simply be due to luck of the draw. Reality check bootstrap test indicate that this is not the case, and the TTR strategies indeed outperform the BH. Overall, we provide compelling evidence that simple technical trading rules offer reduction in left tail risk.

The rest of the paper is organized as follows. Section 2 presents methodology and data. Results are presented in section 3. Section 4 discusses largest loss avoidance. Discussion and robustness are presented in section 5. Section 6 concludes.

2 Methodology and data

2.1 Technical Trading Rules

The TTR in this paper are based on simple moving averages of stock index levels (MA), time-series models (TS) for the return series, and the mix of the two.

The moving average entails that all funds are invested in the stock index when short term moving average of M1 days exceeds long term moving average of M2 days by $p_t d$, where p_t is the index level, and d takes on values of 0 or 0.1%, and in a risk-free rate otherwise. We follow Brock et al. (1992) and use the following combinations to calculate moving averages (M1,M2): (1,50), (1,150), (5,150), (1,200), (2,200).[2]

For example, for a MA(1,50) strategy with $d = 0$, end of day on November 19, 2018, an investor would compare the level of the Dow Jones Industrial Average price (DJIA) with its 50 day moving average. If the current price exceeds the moving average, the decision is then made to invest in the DJIA. An investor would then hold DJIA until such time that the DJIA level falls below the 50 day moving average, at which point the funds are moved to a risk-free rate investment.

For the time-series strategy, the funds are invested in a stock index if the one-step ahead model prediction $R_{t+1} > d$, and in a risk-free rate otherwise. The equity index return at time $t + 1$ (R_{t+1}) is estimated by the following three time-series models: $\mathrm{AR}_{\mathrm{M2}}(1)$, $\mathrm{GARCH}_{\mathrm{M2}}(1,1)$, and $\mathrm{EGARCH}_{\mathrm{M2}}(1,1)$, where M2 is the number of observations used for the estimation of

$$R_t = c + \beta R_{t-1} + \sigma_t Z_t \tag{1}$$

Here Z_t are standard normal innovations. For the $\mathrm{AR}_{\mathrm{M2}}(1)$ models σ_t is constant. For the GARCH and EGARCH models σ_t takes the appropriate form.[3]

[2]For the reality check bootstrap we include any combination of ({1,2,5},{50,150,200}) for the MA strategy. In combination with the two thresholds values for d, this leads to 18 MA strategies.

[3]See Bollerslev (1986) for the GARCH specification, and see Nelson (1991) for the EGARCH specification. For the $\mathrm{AR}_{\mathrm{M2}}(1)$ strategy, we run the model for M2 = 100, 150, 200. To guarantee

In the mixed strategy we combine the signals from the moving average and the time-series strategies. When both strategies give a buy signal, the funds are invested in a stock index, and they only switch into the risk-free rate if both strategies produce a sell signal. We combine the $\mathrm{MA}(\mathrm{M1}, \mathrm{M2})$ signals with the $\mathrm{AR}_{\mathrm{M2}}(1)$ signal.[4]

2.2 Risk measures

Most of the risk metrics we use are standard in the financial literature. Maximum drawdown is a measure mainly used by practitioners to measure the largest single percentage drop from peak to bottom in the value of the investment,

$$\text{Max Drawdown} = \max_{t=1,\ldots,T} \left[\frac{\max\limits_{i=1,\ldots,t} (p_i) - p_t}{\max\limits_{i=1,\ldots,t} (p_i)} \right] \tag{2}$$

Here p_t is the price level at time t, and T is the total number of observations in the sample.

We use an extreme value theory (EVT) framework to study the tails of the return distributions. This framework is well suited to investigate extremely large falls in asset prices. It allows us to determine the Value-at-Risk (VaR) and Expected Shortfall (ES) semi-parametrically.[5] Assuming the tail is regularly varying and

stability of the estimates we only run the GARCH and EGARCH for $\mathrm{M2} = 200$. In combination with the two thresholds values for d, this leads to 10 different time-series strategies.

[4] To ensure estimation stability, the smallest time horizon over which $\mathrm{AR}_{\mathrm{M2}}(1)$ is applied is a 100 days. Therefore, in the mixed strategy we match the $\mathrm{AR}_{100}(1)$ with the smallest M2 from the MA strategies, $\mathrm{M2} = 50$.

[5] See Danielsson et al. (2006) for a detailed description of the EVT methodology.

under the assumption of self-similarity we are able to model the tail as a scaled Pareto distribution. We therefore can derive the semi-parametric VaR estimator for return R as follows:

$$\mathrm{VaR} = P^{-1}(R > x) = \left(\frac{A}{P(R > x)}\right)^{1/\alpha} \tag{3}$$

Here α is the shape parameter, that indicates how heavy the tail of the distribution is, which is estimated by Hill's (1975) estimator. The scaling coefficient A is estimated by inverting the scaled Pareto cumulative distribution function (cdf) at some intermediate quantile x_k,

$$P(R > x_k) = A x_k^{-\alpha_k} \to A = P(R > x_k)\, x_k^{\alpha_k}, \tag{4}$$

where k is the number of observations used for the Hill estimator and P is the empirical cdf, which is substituted by k/n.

The ES is a measure of expected return given that a certain threshold return level is crossed. This threshold is often set at the VaR level. The ES can alternatively be described by the conditional expectation of the returns, leading to:

$$\mathrm{E}(R|\mathrm{VaR}) = \int_{\mathrm{VaR}}^{\infty} \frac{x f(x)}{1 - F(\mathrm{VaR})} dx = \frac{\alpha}{\alpha - 1}\mathrm{VaR} \tag{5}$$

The above formula shows that once VaR is calculated, the ES can be obtained relatively easily.

2.3 Bootstrap and reality check bootstrap

A technical trading rule producing superior performance can be attributed to luck. After all, some trading rules are bound to outperform due to random chance. We address this concern in two ways.

First, using a bootstrap algorithm, we test whether a given strategy significantly outperforms a BH strategy. In this respect we follow the Sullivan et al. (1999) reality check bootstrap, but the strategy is tested in isolation of the other TTR strategies. In the bootstrap, trading signals are resampled with the associated trading strategy returns and BH returns. We use a block resampling procedure to draw the bootstrap samples. Based on these samples, new risk metrics are calculated for the bootstrapped TTR sample and the BH. The difference between the TTR and BH risk-metrics over the different bootstrapped samples gives us the bootstrapped standard errors for the outperformance of the TTR over the BH strategy.[6]

The one-sided p-values for the individual strategies indicate whether the metrics are significantly different from the BH strategy. For the VaR and ES metric we need to adjust the bootstrap procedure. One can argue that the best way to avoid tail risk is to simply invest in a risk-free asset 100% of the time.[7] This is problematic for the bootstrap procedure as the BH will always underperform a TTR strategy on the basis of VaR and ES metrics, which skews the bootstrap

[6]For a detailed description of the bootstrap procedure we refer to Sullivan et al. (1999).

[7]The worst year and maximum drawdown benefit from positive returns and therefore are not affected by this effect.

distribution in favour of rejecting the H_0 of no outperformance. To counter this effect, we randomly allocate an equal number of out signals to the bootstrapped BH returns. The interpretation of this alternative bootstrap is the over performance of the TTR strategy over a random-out strategy. For example, if a TTR strategy results in being out of the market 20% of the time, an appropriate benchmark may be the one that randomly replaces 20% of the BH observations with a risk-free rate.

Given the bootstrap distribution for all the individual strategies, we perform the reality check bootstrap by Sullivan et al. (1999) with the 46 strategies specified above.[8] The reality check tells you if the best performing strategy is significantly better than the benchmark or whether the strategy is just a lucky draw.

3 Data

We apply TTR to a variety of data series. For the main analysis, we use daily closing values of the DJIA, which are obtained from MeasuringWorth for the period from October 7, 1896 till December 31, 2018. We replicate the analysis on 39 national equity indices obtained from WRDS daily world indices. Risk free rate data for the US market is obtained from the Kenneth R. French data library[9] and from the OECD data center for the other countries. Risk measure analysis is restricted to 31 countries due to the lack of availability of risk-free rate data for some of the countries. The US business cycle data is obtained from the NBER. We rely on the OECD turning point data set for other national business cycle data.

[8] There are 18 moving average rules, 10 time-series rules and 18 mixed rules.

[9] For the period before 1925 we set the risk free rate to zero. This will bias the results against the TTR strategy.

Table 8 presents the detailed summary of data series used in this paper.

4 Results

4.1 Technical Trading Rules

Figure 1 gives a visual representation of the performance of the TTR rule relative to a passive BH strategy. Ignoring transaction costs, it is clear from the figure that if a dollar was invested on Wednesday October 7 1896 in the DJIA index with TTR MA(5,150) trading signals you would be better off than the BH strategy.[10] The trading rule frequently avoids drops of 4% in the DJIA, as indicated by the red crosses. Clearly, the figure is starting point dependent and more in-depth analysis is warranted before any conclusions may be drawn about the empirical risks and returns.

We begin by analysing the risk and return profile of the TTR strategies. Results for the MA strategy are presented in Table 1. The results are quite striking. In all MA specifications, Sharpe ratios are higher, maximum drawdowns lower, and worst years returns significantly higher than those corresponding to a BH strategy. Gregory-Allen et al. (2012) show that high returns on a momentum strategy may simply present a compensation for higher left tail risk of those strategies. To be specific, the authors show that the asymmetry between fat left tail and thin right tail strongly reduces momentum strategys utility levels.

[10]The BH strategy results in $889.51 at the end of 2018, as compared to $3,865.50 for the MA(5,150) strategy.

Our results, however, show that this is not the case with the MA strategies. All tail risk measures VaRs and Expected Shortfalls are substantially and significantly lower than those of a BH strategy. For instance, a MA(1,50) strategy has a 2.5% VaR of 1.32%, as opposed to 2.09% for a BH. In general, MA tail risk measures are reduced by about one third. Moreover, tail risk measures remain very stable across trading strategy specifications. For instance, a 2.5% ES ranges from 2.30% for a MA(1,50) strategy to 2.44% for a MA(5,150) strategy. This is substantially lower than the 3.52% expected shortfall of a BH strategy.

Table 1 shows that when it comes to the left tail of the distribution, the MA(1,50) strategy is the best performing strategy. This strategy is very reactive relative to the other TTR. Therefore, in the presence of volatility clustering this strategy is able to adjust quickly.

4.2 Time series and Mixed strategies

The results for time-series strategies are presented in Table 2. The results are largely consistent with those presented in Table 1. Just as with the MA specifications, all time-series specifications produce results superior to a BH strategy. Sharpe ratios are higher (in fact, in some specifications they are higher than those produced by MA strategies), maximum drawdowns are lower, and worst year returns are higher than those for a BH strategy. The p-values show that all metrics significantly outperform a BH, with the exception of maximum drawdown for the GARCH(200) and EGARCH(200) specification and worst year metric for EGARCH(200) specification. All left tail ES and VaR metrics are significantly lower than those of a BH strategy as well (across all specifications).

The mixed strategy results are presented in Table 3. The results are largely consistent with those of MA and time-series strategies. Interestingly, mixed strategy results, although superior to those of a BH strategy, are not superior to either MA or time-series strategies in all instances. As mentioned above, a mixed strategy produces a signal only if both MA and time-series strategies simultaneously and unanimously yield a buy or sell signal. Thus, it may be intuitive to expect a mixed strategys results to be superior to those of individual strategies. Our results, however, do not support this assertion.

4.3 Reality check bootstrap

Table 11 reports the results of the reality check bootstrap. We see that for VaR and ES the most reactive simple moving average strategy shows the best performance. For the Sharpe ratio, the GARCH time-series model has the best performance, and for the worst year metric, the mixed strategy shows the best results. The p-values of the reality check are indistinguishable from zero, providing evidence that our findings are not the result of data snooping.[11] This finding is in line with the results from Sullivan et al. (1999) who report the same result for the expected returns and Sharpe ratios of TTR. We enrich their results by confirming that the same conclusions hold for the ability of TTR in curtailing tail risk.

[11]For VaR and ES we use the alternative bootstrapped benchmark with randomly allocated sell signals to the BH strategy.

5 Avoiding largest losses

We now further investigate how simple TTR strategies lower tail risk measures. One of the most desirable trading strategy outcomes from a practitioners point of view is avoidance of large losses. We refer to the Safety First stream of literature following the seminal article by Roy (1952), which is based on the criterion that the probability of the portfolios return falling below a minimum threshold is minimized. Further, we note that in the presence of margin calls (Brunnermeier and Pedersen, 2008) and limited risk bearing capacity (Siriwardane, 2018) large single losses have negative indirect effects. Panel a of Table 4 reports percentage of negative returns in the DJIA below a certain threshold level that are avoided, as the TTR strategy generates a selling signal (% out). Following Brock et al. (1992) we choose a MA(1,150) strategy. Table 4 also reports the total number of negative returns below a certain threshold level.

We are comparing the percentage of avoided negative shocks to a coin flip scenario of 50%. With the exception of very mild negative shocks (-0.5%), the TTR strategies consistently allow the investor to avoid a high percentage of negative shocks. With the only exception of a negative 1.0% shocks in the 1990-2018 subsample, the percentage of avoided shocks is consistently higher than 50%. The avoided shock percentage increases with the magnitude of a shock, with as much as 88% of shocks of -4.0% or more avoided in the 1990-2018 sub-period.

In order to further investigate the payoff structure of this trading strategy, we use NBER business cycle dates to identify economic recessions. Avoiding large losses is valuable, but avoiding them in time of a recession is more valuable still. Panel b of Table 4 presents the percentage of negative shocks avoided during the NBER recessions. The results are striking in the magnitude of 80% or higher for almost all sub-periods.[12] Almost 90% of shocks of -2.0% or higher are avoided across the entire sample. Even more strikingly, all shocks of -2.5% or greater are avoided in the most recent 1990-2018 sub-period. This result suggests that a simple MA strategy is very attractive for hedging purposes, as it avoids the largest percentage of extreme negative shocks precisely when investors need it most during recessions.

We believe our evidence links the financial markets to the real economy. The TTR strategies lever on the notion that stock markets predict economic growth. Ample empirical evidence exists of a positive relationship between equity prices and future economic growth, see, e.g., Ang (2014, Ch. 7); Chen et al. (1986); Cornell (2010) or Ritter (2005). Our results show that TTR-based strategies likely perform well as long as the economy goes through long cyclical movements. Feedback effects from the real economic cycles translate into stock market valuation changes. Because stock markets are forward looking, a TTR-based strategy will avoid being in the stock market during protracted economic recessions. As a result, the left tail of the return distribution likely is thinner than that of the market. Of course, you can only be certain that the economy is in a recession after it has arrived and after the stock market has already taken a tumble. The TTR strategies use the stock markets predictive power to take a bet that the economy will not recover very quickly and thus that the stock market will also recover slowly. We

[12] In the 1963-1990 period large negative shocks during NBER recessions are rare. Therefore, the percentage of avoided shocks below -2.5% for this subperiod is a very noisy measure.

refer to Ilmanen (2011, Ch. 16), who relates asset returns to the pure fundamentals in the economy, thus (changing views on) GDP and CPI. On a sobering note, as a result, TTR strategies will likely underperform compared to BH, in the event of sudden economic recoveries with accompanying quick share price increases. In such a scenario, TTR strategies are likely to underreact and are still out of the market when stock prices rise, thus reflecting unexpected economic growth shocks.

6 Discussion and robustness

6.1 Transaction costs

An active trading strategy, which TTR is, has a clear disadvantage compared to the BH strategy transaction costs that an investor has to incur every time a buy or sell signal is generated. Tables 5 7 report the results similar to those reported in Tables 1 3, while adding a 0.05% transaction cost per individual buy or sell transaction.[13] The results for the moving average strategy (Table 5) are virtually identical to the ones reported in Table 1, suggesting that transaction costs play only a small part in explaining the results. The results for the time-series strategies, reported in Table 6, are more sobering. While the tail risk measures are only marginally higher than those reported in Table 2, the same cannot be said about Sharpe ratios. In particular, when $d = 0$, meaning that there is no threshold to change the TTR signal, Sharpe ratios become virtually indistinguishable from a BH one (as a matter of fact, for the $\mathrm{AR}_{100}(1)$ strategy, it is below the BH). However, once

[13]Many discount brokers offer a fixed \$ transaction fee for trading in equities. Assuming that the initial investment is sizable, these cost are negligible. Historically this is not the case. Lesmond et al. (2004) report a variable 0.09% + \$254 transaction fee for transactions above \$500,000 in equities.

d is set to 0.1, automatically reducing the number of transactions, Sharpe ratios become substantially higher. Mixed strategy results (Table 7) with transaction costs produce results only marginally worse than those without transaction costs, as you need both MA and TS strategies to produce a trading signal, thus resulting in a relatively low number of transactions. Our results suggest that transaction costs, while affecting Sharpe ratios in some cases, have negligible effect on tail risk measures.

6.2 Changing specifications and samples

Our main results are obtained using the DJIA data. We now replicate the analysis on 31 international equity indices, as well as on sub-samples of DJIA data. The results are presented in Table 9. Our findings are robust. All VaR measures in all specifications outperform the respective BH measures in all of the international markets and DJIA subsamples. Expected shortfall measures are nearly uniformly superior to BH ones. Minor exceptions are China, Greece, and DJIA in the sub-period of 1963-1990, where outperformance depends on a trading strategy specification.

Table 10 reports percentage of avoided shocks across different national indices, following the format of Table 4. We report the results for the whole sample, as well as during recessions that we now use all 39 international indices, as we do not need a risk-free rate to perform this analysis and thus can use the full data set.[14]

[14]For most countries the OECD provides business cycle data. For the exceptions Hong Kong, Columbia and Egypt, we use the NBER US cycle as a proxy. For the other four exceptions Singapore, Taiwan, Malaysia, and the Philippines, we use the major five Asian countries category from the OECD data. In unreported results, we have exclusively used US business cycles for the

Several observations are interesting. Percentage of avoided shocks is almost always higher in recessions than in the overall sample, indicating that TTR provide better tail risk protection in recessions. Another interesting observation is that the percentage of avoided shocks increases monotonically with the shock magnitude. For instance, in only 7 out of 39 countries are we able to avoid more than 50% of shocks of a magnitude of -0.5% or lower. The number increases to 18 out of 39 for shocks of -1.0% or lower, and to 31 out of 39 for shocks of -1.5% or lower. The only consistent exceptions are China and India, where the percentage of avoided shocks tends to stay below 50%. Overall, our evidence is consistent with the results reported in Table 4 following a TTR strategy will result in avoidance of a high percentage of negative shocks, with that percentage being higher in recessions.

6.3 Other considerations

One may wonder why, if financial markets are efficient, our empirical TTR results are as strong as we report them to be. Of course, (time-varying) risk may be the reason for the findings, but our results show that the TTR strategies actually reduce the investment risk. And even more so during the periods when it matters most, namely during protracted economic downturns when other asset prices are likely to fall as well. Hence, risk is not a logical candidate explanation of our findings.

Literature offers several other potential explanations for our apparent counter-intuitive results. First, we note that as an investor gains from reduced left tail exposure, the right tail is reduced as well returns in the best year (not reported

analysis. Qualitatively the results are very similar.

in the tables) are always lower in all TTR specifications than for BH strategy. Apparently, as a result of the TTR signals, the investor inadvertently misses out on some of the upward stock market moves. Thus, not all effects of the TTR strategies are positive.

Second, we note that a potential limit to arbitrage exists . Following a TTR strategy likely is not feasible for large institutional investors, such as pension funds and mutual funds. Mechanically adhering to the TTR signals would entail far too large swings in the portfolio. Such large changes in asset allocation will, in many cases, be difficult to implement because of liquidity considerations. Moreover, many large investors are forbidden from moving out of long term asset allocations, which are linked to their long term goals or even to their investment statutes. In other cases, strong asset allocation swings would not be allowed because of non-compliance with supervisory risk management and prudent person rules that apply to such funds. Besides these rules-based arguments against (tactical) asset allocation changes, softer arguments also hold. It is difficult for a portfolio manager to explain to its fund investors or to its pension fund beneficiaries that equity exposure is trimmed just because a black box technical rule is followed. The portfolio manager would run a severe career risk, as well as need a very strong governance framework to stick to its TTR strategy. Long protracted economic downturns do not occur very often and it thus may take many years for the TTR strategies to prove their value to investors which in practice may make the phenomenon difficult to arbitrage away.

Third, although the historical observation period is long and the results are stable over time, there is no guarantee that they will remain so in the future. Research has shown that the empirical strength of asset return predictability tends to strongly reduce after publication date, see Arnott et al. (2019); Hou et al. (2018); Linnainmaa and Roberts (2018) or McLean and Pontiff (2016). Our reported conclusions may dissipate in the future just as well and thus prove to be a temporary phenomenon only.

Finally, although some of our findings seem to run counter to the notion that markets are (mostly) efficient, which is arguably one of the pillars of finance, we note that many of our findings do find support in the literature. The existence of momentum in financial markets is evidenced in an abundant literature. Likewise is the link between financial markets and the real economy evidenced in many papers. Seen from this perspective, our study contains no surprises. Our real contribution lies in the focus on the tails and in the strength of our results, while simultaneously linking them to protracted economic recessions.

7 Conclusion

Technical trading rules-based strategies in equity markets outperform a buy-and-hold strategy on a number of dimensions. Not only are the Sharpe ratios higher in virtually all specifications and samples, but also left tail exposure is reduced substantially. Following a simple moving average strategy, an investor would be able to avoid a large percentage of negative shocks. Left tail exposure is reduced even further during NBER recessions, which we attribute to feedback effects between financial markets and real economy. Our results are remarkably robust and warrant further investigation of various trading strategies from the perspective of left tail risk reduction.

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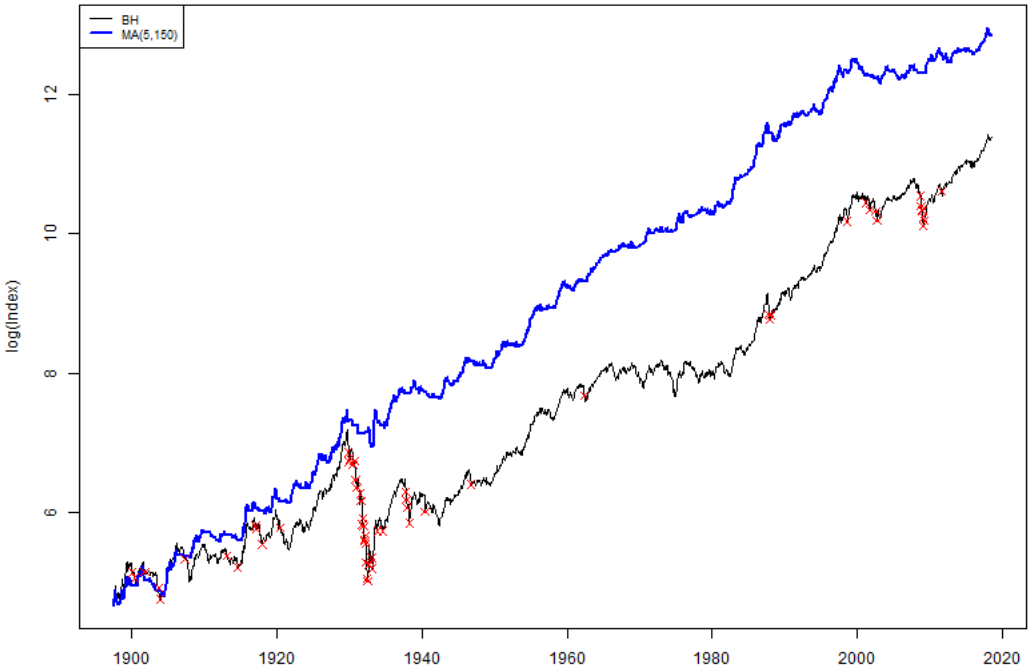
A Figures

Figure 1: Buy-and-hold versus MA(5,150)



This figure shows the performance of the BH strategy (thin black) and the TTR MA(5,150) rule (thick blue) over the whole sample period for the DJIA. The red crosses are negative daily returns of 4% or more in the BH strategy which are avoided by the TTR strategy implementation.

B Tables

Table 1: Risk measures of moving average rules

	BH	(1,50)		(1,150)		(5,150)		(1,200)		(2,200)	
d		0	0.1%	0	0.1%	0	0.1%	0	0.1%	0	0.1%
SR	0.25	0.53	0.51	0.47	0.46	0.42	0.42	0.49	0.49	0.46	0.45
	-	(0)	(0)	(0)	(0)	(0.02)	(0.02)	(0)	(0)	(0)	(0)
MDD	89.19	45.37	45.41	43.84	45.12	40.85	41.75	39.75	42.82	46.31	45.36
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Worst year	-54.13	-20.32	-20.32	-21.66	-21.91	-17.97	-17.73	-20.31	-21.35	-30.18	-30.18
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 2.5%	2.09	1.32	1.33	1.38	1.38	1.40	1.40	1.39	1.39	1.40	1.41
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 1.0%	3.03	1.95	1.95	2.03	2.04	2.07	2.07	2.05	2.05	2.07	2.07
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR0.05%	4.03	2.62	2.62	2.73	2.74	2.78	2.79	2.76	2.75	2.78	2.77
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 2.5%	3.52	2.30	2.30	2.40	2.40	2.43	2.44	2.42	2.41	2.43	2.42
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 1.0%	5.12	3.39	3.39	3.54	3.54	3.59	3.61	3.56	3.55	3.59	3.56
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 0.5%	6.79	4.55	4.55	4.76	4.77	4.82	4.85	4.78	4.77	4.82	4.78
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)

This table reports statistics on performance and risk for moving average trading strategies. The first row presents trading strategy specifications. BH denotes a buy-and-hold strategy. The first and second numbers in brackets are the number of trading days for the short and long moving average, respectively. The second row indicates by which percentage of the price level the moving averages should differ to produce a trading signal. The first column in the table denotes the various performance metrics. SR is the Sharpe ratio. MDD is the maximum drawdown. Worst year is the worst calendar year return in the sample. The Value-at-Risk (VaR) and Expected Shortfall (ES) are calculated semi-parametrically with an extreme value approach. The numbers in brackets are the bootstrapped one-sided p-values. The data are daily DJIA levels from October 7, 1896 till 31 December, 2018.

Table 2: Risk measures of time-series rules

	BH	AR(100)		AR(150)		AR(200)		GARCH(200)		EGARCH(200)	
d		0	0.1%	0	0.1%	0	0.1%	0	0.1%	0	0.1%
SR	0.25	0.49	0.48	0.59	0.50	0.60	0.49	0.62	0.48	0.62	0.46
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
MDD	89.19	67.65	68.42	57.10	63.64	59.80	65.30	71.63	74.01	76.67	68.05
	-	(0.05)	(0.06)	(0)	(0)	(0)	(0.01)	(0.16)	(0.11)	(0.68)	(0.01)
Worst year	-54.13	-34.36	-34.78	-27.66	-30.08	-25.31	-31.26	-32.43	-33.67	-44.19	-29.84
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0.13)	(0)
VaR 2.5%	2.09	1.46	1.45	1.45	1.45	1.49	1.49	1.60	1.65	1.44	1.47
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 1.0%	3.03	2.18	2.17	2.17	2.18	2.25	2.25	2.40	2.47	2.21	2.24
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR0.05%	4.03	2.97	2.94	2.95	2.97	3.07	3.08	3.27	3.34	3.06	3.08
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 2.5%	3.52	2.62	2.59	2.59	2.61	2.71	2.71	2.87	2.94	2.70	2.71
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 1.0%	5.12	3.93	3.87	3.88	3.92	4.09	4.11	4.31	4.38	4.15	4.13
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 0.5%	6.79	5.35	5.25	5.27	5.34	5.59	5.63	5.87	5.94	5.74	5.69
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)

This table reports statistics on performance and risk for time-series trading strategies. The first row presents trading strategy specifications. BH denotes a buy-and-hold strategy. The first and second numbers in brackets are the number of trading days for the short and long moving average, respectively. The second row indicates by which percentage of the price level the moving averages should differ to produce a trading signal. The first column in the table denotes the various performance metrics. SR is the Sharpe ratio. MDD is the maximum drawdown. Worst year is the worst calendar year return in the sample. The Value-at-Risk (VaR) and Expected Shortfall (ES) are calculated semi-parametrically with an extreme value approach. The numbers in brackets are the bootstrapped one-sided p-values. The data are daily DJIA levels from October 7, 1896 till 31 December, 2018.

Table 3: Risk measures of mixed rules

	BH	(1,50)		(1,150)		(5,150)		(1,200)		(2,200)	
d		0	0.1%	0	0.1%	0	0.1%	0	0.1%	0	0.1%
SR	0.25	0.50	0.47	0.47	0.51	0.45	0.49	0.50	0.45	0.48	0.43
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0.01)
MDD	89.19	54.57	45.76	43.55	33.83	35.17	33.16	36.83	53.50	39.70	54.38
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Worst year	-54.13	-26.94	-25.34	-28.42	-21.72	-20.07	-21.72	-20.63	-24.47	-21.10	-24.47
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 2.5%	2.09	1.33	1.37	1.40	1.40	1.41	1.41	1.41	1.43	1.42	1.43
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 1.0%	3.03	1.97	2.02	2.07	2.07	2.08	2.09	2.07	2.12	2.09	2.13
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR0.05%	4.03	2.66	2.73	2.79	2.79	2.80	2.81	2.77	2.87	2.80	2.87
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 2.5%	3.52	2.33	2.39	2.44	2.44	2.46	2.46	2.43	2.52	2.45	2.52
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 1.0%	5.12	3.45	3.54	3.61	3.62	3.63	3.64	3.57	3.74	3.62	3.75
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 0.5%	6.79	4.65	4.77	4.85	4.87	4.88	4.90	4.79	5.06	4.86	5.06
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)

This table reports statistics on performance and risk for "mixed" trading strategies. The trading signals for the mixed trading strategy are the combination of the moving average and time-series trading strategies. The first row presents trading strategy specifications. BH denotes a buy-and-hold strategy. The first and second numbers in brackets are the number of trading days for the short and long moving average, respectively. The second row indicates by which percentage of the price level the moving averages should differ to produce a trading signal. The first column in the table denotes the various performance metrics. SR is the Sharpe ratio. MDD is the maximum drawdown. Worst year is the worst calendar year return in the sample. The Value-at-Risk (VaR) and Expected Shortfall (ES) are calculated semi-parametrically with an extreme value approach. The numbers in brackets are the bootstrapped one-sided p-values. The data are daily DJIA levels from October 7, 1896 till 31 December, 2018.

Table 4: Large negative shocks of DJIA

	1896-2018		1896-1927		1927-1963		1963-1990		1990-2018	
	% out	Shocks	% out	Shocks	% out	Shocks	% out	Shocks	% out	Shocks
-0.5 %	0.45	7,648	0.49	2,154	0.47	2,210	0.48	1,578	0.36	1,601
-1 %	0.53	3,682	0.55	1,032	0.56	1,149	0.51	649	0.47	798
-1.5 %	0.59	1,808	0.62	486	0.62	639	0.55	256	0.54	405
-2 %	0.65	978	0.61	256	0.67	409	0.64	94	0.65	212
-2.5 %	0.71	554	0.65	130	0.72	274	0.72	39	0.76	106
-3 %	0.71	350	0.59	71	0.73	192	0.65	20	0.78	65
-3.5 %	0.73	241	0.61	44	0.73	139	0.62	13	0.87	45
-4 %	0.74	163	0.62	26	0.73	97	0.62	8	0.88	32

(a) All negative shocks

	1896-2018		1896-1927		1927-1963		1963-1990		1990-2018	
	% out	Shocks	% out	Shocks	% out	Shocks	% out	Shocks	% out	Shocks
-0.5 %	0.74	2,257	0.70	891	0.76	767	0.76	325	0.81	227
-1 %	0.80	1,305	0.80	428	0.81	514	0.77	174	0.87	156
-1.5 %	0.84	749	0.84	199	0.83	345	0.85	86	0.89	103
-2 %	0.87	459	0.90	102	0.84	252	0.87	38	0.92	62
-2.5 %	0.88	296	0.94	50	0.84	186	0.88	16	1	41
-3 %	0.87	200	0.92	24	0.84	140	0.75	4	1	30
-3.5 %	0.89	144	0.93	15	0.86	103	0.50	2	1	24
-4 %	0.89	100	1	7	0.85	73		0	1	20

(b) Negative shocks in NBER defined recessions

This table reports the percentage of negative shocks which are avoided due to the trading strategy. In this table we utilizes MA(1,150) trading rule. The first row states the time period of the sample for the DJIA index. The column "% out" indicates the percentage of shocks that are avoided. The column "Shocks" reports the total number of shocks observed.

Table 5: Risk measures moving of average rules (with transaction costs)

	BH	(1,50)		(1,150)		(5,150)		(1,200)		(2,200)	
d		0	0.1%	0	0.1%	0	0.1%	0	0.1%	0	0.1%
SR	0.25	0.44	0.43	0.42	0.42	0.39	0.39	0.45	0.45	0.43	0.43
	-	(0.09)	(0.09)	(0.06)	(0.05)	(0.06)	(0.06)	(0.01)	(0.01)	(0.02)	(0.02)
MDD	89.19	47.00	47.04	46.36	47.58	41.31	42.21	42.59	45.33	47.35	46.12
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Worst year	-54.13	-21.51	-21.38	-23.17	-23.41	-18.76	-18.42	-21.84	-22.86	-30.73	-30.73
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 2.5%	2.09	1.34	1.34	1.39	1.39	1.40	1.41	1.40	1.40	1.41	1.41
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 1.0%	3.03	1.98	1.98	2.04	2.04	2.07	2.08	2.06	2.06	2.07	2.07
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR0.05%	4.03	2.67	2.66	2.74	2.75	2.78	2.79	2.77	2.76	2.78	2.78
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 2.5%	3.52	2.34	2.33	2.40	2.41	2.43	2.45	2.42	2.42	2.44	2.43
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 1.0%	5.12	3.47	3.44	3.54	3.55	3.59	3.62	3.56	3.56	3.59	3.58
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 0.5%	6.79	4.67	4.63	4.76	4.76	4.81	4.86	4.78	4.78	4.82	4.80
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)

This table reports statistics on performance and risk for moving average trading strategies, including 0.06% transaction costs. The first row presents trading strategy specifications. BH denotes a buy-and-hold strategy. The first and second numbers in brackets are the number of trading days for the short and long moving average, respectively. The second row indicates by which percentage of the price level the moving averages should differ to produce a trading signal. The first column in the table denotes the various performance metrics. SR is the Sharpe ratio. MDD is the maximum drawdown. Worst year is the worst calendar year return in the sample. The Value-at-Risk (VaR) and Expected Shortfall (ES) are calculated semi-parametrically with an extreme value approach. The numbers in brackets are the bootstrapped one-sided p-values. The data are daily DJIA levels from October 7, 1896 till 31 December, 2018.

Table 6: Risk measures of time-series rules (with transaction costs)

	BH	AR(100)		AR(150)		AR(200)		GARCH(200)		EGARCH(200)	
d		0	0.1%	0	0.1%	0	0.1%	0	0.1%	0	0.1%
SR	0.25	0.18	0.38	0.28	0.42	0.29	0.41	0.36	0.40	0.29	0.35
	-	(1)	(0.34)	(1)	(0.14)	(1)	(0.13)	(1)	(0.1)	(1)	(0.57)
MDD	89.19	71.74	70.30	63.30	66.13	66.20	67.41	75.19	75.45	79.88	69.55
	-	(0.2)	(0.12)	(0)	(0.03)	(0.03)	(0.03)	(0.39)	(0.2)	(0.88)	(0.04)
Worst year	-54.13	-35.74	-36.18	-30.24	-31.01	-26.25	-32.51	-33.51	-35.47	-46.47	-31.22
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0.37)	(0)
VaR 2.5%	2.09	1.48	1.46	1.48	1.47	1.51	1.50	1.63	1.67	1.47	1.48
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 1.0%	3.03	2.22	2.19	2.20	2.20	2.27	2.27	2.43	2.48	2.24	2.26
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR0.05%	4.03	3.01	2.97	2.98	2.99	3.10	3.12	3.29	3.35	3.08	3.11
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 2.5%	3.52	2.65	2.61	2.62	2.63	2.72	2.75	2.89	2.94	2.72	2.75
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 1.0%	5.12	3.96	3.90	3.91	3.93	4.09	4.17	4.32	4.37	4.14	4.18
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 0.5%	6.79	5.39	5.30	5.30	5.35	5.58	5.71	5.85	5.91	5.70	5.76
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)

This table reports statistics on performance and risk for time-series trading strategies, including 0.06% transaction costs. The first row presents trading strategy specifications. BH denotes a buy-and-hold strategy. The first and second numbers in brackets are the number of trading days for the short and long moving average, respectively. The second row indicates by which percentage of the price level the moving averages should differ to produce a trading signal. The first column in the table denotes the various performance metrics. SR is the Sharpe ratio. MDD is the maximum drawdown. Worst year is the worst calendar year return in the sample. The Value-at-Risk (VaR) and Expected Shortfall (ES) are calculated semi-parametrically with an extreme value approach. The numbers in brackets are the bootstrapped one-sided p-values. The data are daily DJIA levels from October 7, 1896 till 31 December, 2018.

Table 7: Risk measures of mixed rules (with transaction costs)

	BH	(1,50)		(1,150)		(5,150)		(1,200)		(2,200)	
d		0	0.1%	0	0.1%	0	0.1%	0	0.1%	0	0.1%
SR	0.25	0.44	0.44	0.44	0.49	0.43	0.48	0.48	0.44	0.47	0.42
	-	(0.04)	(0.02)	(0.01)	(0)	(0.01)	(0)	(0)	(0.01)	(0)	(0.01)
MDD	89.19	55.16	46.28	44.90	34.16	36.00	33.69	36.99	53.61	41.08	54.49
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Worst year	-54.13	-27.21	-25.92	-29.19	-21.87	-20.55	-21.87	-21.97	-24.52	-21.96	-24.52
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 2.5%	2.09	1.34	1.37	1.41	1.40	1.41	1.41	1.41	1.43	1.42	1.43
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 1.0%	3.03	1.99	2.04	2.08	2.07	2.09	2.09	2.08	2.12	2.09	2.13
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR0.05%	4.03	2.69	2.75	2.79	2.78	2.81	2.81	2.78	2.87	2.81	2.88
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 2.5%	3.52	2.36	2.41	2.44	2.44	2.46	2.46	2.44	2.52	2.46	2.53
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 1.0%	5.12	3.51	3.58	3.60	3.60	3.63	3.64	3.59	3.75	3.63	3.75
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 0.5%	6.79	4.74	4.83	4.84	4.84	4.88	4.91	4.81	5.08	4.88	5.07
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)

This table reports statistics on performance and risk for "mixed" trading strategies, including 0.06% transaction costs. The trading signals for the mixed trading strategy are the combination of the moving average and time-series trading strategies. The first row presents trading strategy specifications. BH denotes a buy-and-hold strategy. The first and second numbers in brackets are the number of trading days for the short and long moving average, respectively. The second row indicates by which percentage of the price level the moving averages should differ to produce a trading signal. The first column in the table denotes the various performance metrics. SR is the Sharpe ratio. MDD is the maximum drawdown. Worst year is the worst calendar year return in the sample. The Value-at-Risk (VaR) and Expected Shortfall (ES) are calculated semi-parametrically with an extreme value approach. The numbers in brackets are the bootstrapped one-sided p-values. The data are daily DJIA levels from October 7, 1896 till 31 December, 2018.

Table 8: Data summary

Name	Data Source	Start	End
Australia Equity Index	WRDS world Index	1986-07	2018-04
Austria Equity Index	WRDS world Index	1999-07	2018-04
Belgium Equity Index	WRDS world Index	1999-07	2018-04
Brazil Equity Index	WRDS world Index	1995-07	2018-04
Switzerland Equity Index	WRDS world Index	1986-07	2018-04
Chile Equity Index	WRDS world Index	2002-02	2018-04
China Equity Index	WRDS world Index	1994-07	2018-04
Colombia Equity Index	WRDS world Index	2005-07	2018-04
Czech Republic Equity Index	WRDS world Index	1995-07	2002-06
Germany Equity Index	WRDS world Index	1999-07	2018-04
Denmark Equity Index	WRDS world Index	1986-07	2018-04
Egypt Equity Index	WRDS world Index	2000-01	2018-04
Spain Equity Index	WRDS world Index	1999-07	2018-04
Finland Equity Index	WRDS world Index	1999-07	2018-04
France Equity Index	WRDS world Index	1999-07	2018-04
United Kingdom Equity Index	WRDS world Index	1986-07	2018-04
Greece Equity Index	WRDS world Index	2001-07	2018-04
Hong Kong Equity Index	WRDS world Index	1986-07	2018-04
Hungary Equity Index	WRDS world Index	1996-07	2018-04
Indonesia Equity Index	WRDS world Index	1990-07	2018-04
India Equity Index	WRDS world Index	1993-07	2018-04
Ireland Equity Index	WRDS world Index	1999-07	2018-04
Italy Equity Index	WRDS world Index	1999-07	2018-04
Japan Equity Index	WRDS world Index	1986-07	2018-04
South Korea Equity Index	WRDS world Index	1988-07	2018-04
Mexico Equity Index	WRDS world Index	1993-07	2018-04
Malaysia Equity Index	WRDS world Index	1989-07	2018-04
Netherlands Equity Index	WRDS world Index	1999-07	2018-04
Norway Equity Index	WRDS world Index	1988-07	2018-04
New Zealand Equity Index	WRDS world Index	1991-07	2018-04
Philippines Equity Index	WRDS world Index	1992-07	2018-04
Poland Equity Index	WRDS world Index	1995-07	2018-04
Portugal Equity Index	WRDS world Index	1999-07	2018-04
Singapore Equity Index	WRDS world Index	1986-07	2018-04
Sweden Equity Index	WRDS world Index	1986-07	2018-04
Thailand Equity Index	WRDS world Index	1988-07	2018-04
Turkey Equity Index	WRDS world Index	2006-02	2018-04
Taiwan Equity Index	WRDS world Index	1988-07	2018-04
South Africa Equity Index	WRDS world Index	2002-06	2018-04
Dow jones industrial average	Measuring Worth (w)	1896-10	2018-07
One-month Treasury bill rate	Kenneth R. French library (w)	1926-07	2018-08
International short term interest rates	OECD Data (w)	1956-01	2018-08
International Turning Points Data	OECD Data (w)	1947-02	2018-12

This table presents source and range of the various data series used in this paper. In the data source column "w" indicates that the data is downloaded from a website.

Table 9: Strategy comparison across samples.

	SR	MDD	Worst year	VaR 2.5%	VaR 1.0%	VaR 0.05%	ES 2.5%	ES 1.0%	ES 0.5%
Australia	Some	All	All	All	All	All	All	All	All
Austria	All	All	All	All	All	All	All	All	All
Belgium	All	All	All	All	All	All	All	All	All
Switzerland	All	All	All	All	All	All	All	All	All
Chile	All	All	All	All	All	All	All	All	All
China	Some	All	All	All	All	All	Some	Some	Some
Colombia	All	All	All	All	All	All	All	All	All
Czech Republic	All	All	All	All	All	All	All	All	All
Germany	All	All	All	All	All	All	All	All	All
Denmark	All	All	All	All	All	All	All	All	All
Spain	Some	All	All	All	All	All	All	All	All
Finland	Some	Some	All	All	All	All	All	All	All
France	Some	All	All	All	All	All	All	All	All
United Kingdom	All	All	All	All	All	All	All	All	All
Greece	All	All	All	All	All	All	All	All	Some
Hungary	Some	All	All	All	All	All	All	All	All
Indonesia	All	All	All	All	All	All	All	All	All
India	All	All	All	All	All	All	All	All	All
Ireland	All	All	All	All	All	All	All	All	All
Italy	Some	All	All	All	All	All	All	All	All
Japan	All	All	All	All	All	All	All	All	All
South Korea	All	All	All	All	All	All	All	All	All
Mexico	Some	All	Some	All	All	All	All	All	All
Netherlands	All	All	All	All	All	All	All	All	All
Norway	All	All	All	All	All	All	All	All	All
New Zealand	Some	All	All	All	All	All	All	All	All
Poland	All	All	All	All	All	All	All	All	All
Portugal	All	All	All	All	All	All	All	All	All
Sweden	All	All	All	All	All	All	All	All	All
South Africa	Some	All	Some	All	All	All	All	All	All
USA (DJIA)	All	All	All	All	All	All	All	All	All
DJIA 1896-1927	Some	All	All	All	All	All	All	All	All
DJIA 1927-1963	All	All	All	All	All	All	All	All	All
DJIA 1963-1990	All	All	All	All	All	All	All	Some	Some
DJIA 1990-2018	Some	All	All	All	All	All	All	All	All

This table presents strategy performance comparison across different data series. All means that all strategy specifications outperform a buy-and-hold. This includes the moving average, time-series and mixed trading strategies. Some and None are defined in a similar way.

Table 10: Avoiding largest losses across various countries

		Shock magnitude							
Country	Period	-0.5 %	-1 %	-1.5 %	-2 %	-2.5 %	-3 %	-3.5 %	-4 %
Australia	All	0.38	0.48	0.55	0.63	0.75	0.74	0.83	0.84
	Recessions	0.45	0.57	0.62	0.69	0.82	0.76	0.79	0.78
Austria	All	0.40	0.50	0.57	0.69	0.75	0.81	0.84	0.84
	Recessions	0.51	0.61	0.70	0.80	0.88	0.88	0.92	0.92
Belgium	All	0.40	0.53	0.64	0.71	0.77	0.86	0.89	0.96
	Recessions	0.65	0.79	0.88	0.91	0.95	0.98	0.97	0.96
Brazil	All	0.42	0.45	0.48	0.55	0.61	0.65	0.68	0.72
	Recessions	0.55	0.59	0.64	0.72	0.81	0.87	0.91	0.92
Switzerland	All	0.45	0.56	0.65	0.72	0.76	0.85	0.88	0.89
	Recessions	0.63	0.74	0.82	0.88	0.88	0.91	0.92	0.94
Chile	All	0.38	0.49	0.57	0.69	0.86	0.85	0.77	0.73
	Recessions	0.57	0.66	0.72	0.77	1	1	1	1
China	All	0.53	0.54	0.52	0.49	0.45	0.44	0.42	0.39
	Recessions	0.65	0.64	0.64	0.61	0.58	0.57	0.52	0.49
Colombia	All	0.47	0.54	0.60	0.64	0.58	0.68	0.90	1
	Recessions	0.82	0.85	0.87	0.89	0.93	0.92	0.89	1
Czech Republic	All	0.58	0.63	0.66	0.71	0.73	0.86	0.92	0.88
	Recessions	0.66	0.72	0.78	0.80	0.83	0.92	1	1
Germany	All	0.47	0.54	0.64	0.68	0.76	0.90	1	1
	Recessions	0.59	0.65	0.74	0.80	0.87	0.91	1	1
Denmark	All	0.37	0.45	0.54	0.59	0.66	0.73	0.68	0.72
	Recessions	0.48	0.60	0.69	0.73	0.78	0.85	0.84	0.82
Egypt	All	0.36	0.43	0.45	0.51	0.50	0.55	0.67	0.66
	Recessions	0.84	0.87	0.84	0.86	0.89	0.90	0.96	1
Spain	All	0.49	0.58	0.66	0.74	0.82	0.87	0.94	0.94
	Recessions	0.61	0.70	0.78	0.85	0.88	0.90	0.95	0.96
Finland	All	0.42	0.49	0.56	0.60	0.66	0.70	0.73	0.76
	Recessions	0.58	0.67	0.72	0.76	0.79	0.82	0.82	0.85
France	All	0.47	0.57	0.66	0.71	0.79	0.90	0.95	0.96
	Recessions	0.71	0.77	0.82	0.86	0.90	0.93	0.97	0.96
United Kingdom	All	0.40	0.49	0.60	0.70	0.78	0.86	0.90	0.93
	Recessions	0.49	0.58	0.76	0.81	0.81	0.90	0.91	0.94
Greece	All	0.60	0.65	0.70	0.72	0.75	0.79	0.81	0.86
	Recessions	0.79	0.81	0.83	0.84	0.86	0.91	0.91	0.96
Hong Kong	All	0.39	0.45	0.51	0.55	0.59	0.61	0.60	0.61
	Recessions	0.75	0.78	0.78	0.79	0.86	0.87	0.82	0.77
Hungary	All	0.39	0.43	0.48	0.53	0.58	0.62	0.65	0.66
	Recessions	0.58	0.64	0.73	0.81	0.81	0.84	0.89	0.88
Indonesia	All	0.40	0.46	0.49	0.55	0.58	0.61	0.63	0.64
	Recessions	0.56	0.63	0.67	0.75	0.77	0.76	0.83	0.85
India	All	0.45	0.46	0.51	0.52	0.51	0.49	0.50	0.49
	Recessions	0.59	0.60	0.65	0.65	0.67	0.65	0.63	0.59
Ireland	All	0.39	0.48	0.56	0.61	0.68	0.76	0.78	0.80
	Recessions	0.45	0.56	0.64	0.71	0.76	0.85	0.88	0.91

Italy	All	0.52	0.61	0.67	0.72	0.79	0.86	0.90	0.93
	Recessions	0.79	0.85	0.89	0.90	0.92	0.95	0.95	0.94
Japan	All	0.55	0.61	0.66	0.67	0.70	0.69	0.74	0.75
	Recessions	0.65	0.70	0.76	0.81	0.86	0.84	0.87	0.85
South Korea	All	0.51	0.55	0.59	0.62	0.64	0.67	0.69	0.72
	Recessions	0.67	0.73	0.79	0.86	0.89	0.91	0.93	0.94
Mexico	All	0.36	0.42	0.47	0.55	0.63	0.67	0.76	0.81
	Recessions	0.61	0.67	0.74	0.82	0.89	0.92	0.94	0.91
Malaysia	All	0.48	0.58	0.63	0.66	0.64	0.64	0.60	0.51
	Recessions	0.65	0.80	0.84	0.88	0.90	0.88	0.85	0.81
Netherlands	All	0.45	0.56	0.66	0.71	0.83	0.91	0.90	0.97
	Recessions	0.64	0.71	0.80	0.86	0.93	0.96	0.96	1
Norway	All	0.38	0.45	0.53	0.60	0.68	0.75	0.77	0.76
	Recessions	0.52	0.61	0.67	0.72	0.80	0.90	0.90	0.92
New Zealand	All	0.35	0.42	0.50	0.47	0.47	0.46	0.42	0.44
	Recessions	0.47	0.56	0.63	0.63	0.58	0.45	0.50	0.50
Philippines	All	0.45	0.49	0.54	0.56	0.64	0.64	0.64	0.64
	Recessions	0.62	0.70	0.80	0.84	0.94	0.95	0.97	0.95
Poland	All	0.40	0.46	0.53	0.54	0.60	0.64	0.67	0.62
	Recessions	0.61	0.68	0.76	0.77	0.83	0.85	0.86	0.86
Portugal	All	0.54	0.61	0.72	0.79	0.85	0.88	0.87	0.87
	Recessions	0.70	0.78	0.87	0.93	0.96	1	1	1
Singapore	All	0.47	0.55	0.62	0.65	0.69	0.72	0.74	0.82
	Recessions	0.65	0.76	0.84	0.92	0.92	0.94	0.97	0.96
Sweden	All	0.40	0.50	0.57	0.65	0.69	0.71	0.73	0.71
	Recessions	0.62	0.72	0.79	0.84	0.86	0.87	0.88	0.83
Thailand	All	0.46	0.51	0.55	0.56	0.61	0.63	0.64	0.64
	Recessions	0.59	0.65	0.68	0.73	0.77	0.79	0.82	0.83
Turkey	All	0.37	0.42	0.49	0.57	0.58	0.65	0.63	0.64
	Recessions	0.64	0.70	0.75	0.88	0.88	0.88	0.88	0.88
Taiwan	All	0.50	0.56	0.59	0.63	0.63	0.63	0.67	0.73
	Recessions	0.62	0.66	0.68	0.71	0.71	0.67	0.68	0.77
South Africa	All	0.24	0.32	0.39	0.51	0.62	0.72	0.79	0.92
	Recessions	0.47	0.56	0.67	0.73	0.83	0.91	1	1

This table presents the percentage of avoided negative shocks for a MA(1,150) strategy across different equity indices. The second column in the table indicates whether the percentage of avoided negative shocks is during the whole sample period, the row indicated by "All", or only during recessions, indicated by "Recessions". The recessions are country specific. We use the OECD data turning points data set to identify the recessions.

Table 11: Reality check bootstrap

	Strategy	Performance	P-Value
Sharp Ratio	Garch(200) $d = 0$	0.62	0
Max Drawdown	MA(5,50) $d = 0.1$	33.00	0
Worst year	Mixed (5,200) $d = 0$	-17.49	0
VaR 2.5%	MA(1,50) $d = 0$	1.32	0
VaR 1.0%	MA(1,50) $d = 0$	1.95	0
VaR0.05%	MA(1,50) $d = 0$	2.62	0
ES 2.5%	MA(1,50) $d = 0$	2.30	0
ES 1.0%	MA(1,50) $d = 1$	3.39	0
ES 0.5%	MA(1,50) $d = 1$	4.55	0

This table presents the results of a reality check bootstrap by Sullivan et al. (1999). The first column reports the risk metrics. The second column indicates the best performing strategy out of our universe of strategies. The third column gives the performance of this strategy and the last column provides the one-sided reality check p-values. The benchmark in the bootstrap is the BH strategy. Additionally, for the VaR and ES metrics we randomly replace observations with the risk-free rate. We do this for the number of times the tested TTR step out of the index for the bootstrapped TTR.