Technical Trading Rules, Loss Avoidance, and The Business Cycle

Abstract

We show that simple technical trading rule (TTR) strategies substantially reduce investment left tail risk. An investor following a TTR strategy can also avoid a high percentage of extremely negative returns. This percentage increases substantially during recessions. Interestingly, tail risk reduction does not come at a cost of lower performance – risk adjusted returns of TTR strategies are in fact higher than those of a buy-and-hold strategy. Our findings are robust to changes in trading strategy specifications. They hold in 38 international equity markets, as well as in a large sample of individual US stocks, and survive a reality check bootstrap.

JEL Codes: G1, G11, G14

Keywords: tail risk; technical trading rules; loss avoidance

1. Introduction

Technical trading rules (TTR) are commonly used by active traders.[1] Numerous researchers have addressed the potential profitability of technical trading strategies.[2] Whether they are indeed superior is still a matter of debate. On one hand, Brock et al. (1992) find significant support for moving average strategies. On the other hand, 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 outperformance of technical trading strategies from 1987 to 2011, Bley and Saad (2020), who document very limited outperformance in MENA markets, and Taylor (2014), who reports that TTR profits are confined to particular episodes in mid-1960s to mid-1980s. Further, Huang and Huang (2020) find that moving average strategies on US indices and ETFs have lower average returns and Sharpe ratios than a buy-and-hold strategy, but higher factor-adjusted performance measures. Some of the reasons for potential profitability of technical trading rules could be attributed to initial under-reaction and delayed over-reaction to news releases (Moskowitz et al., 2012) which, in turn, have several explanations in behavioural finance literature.

Our focus is on the ability of TTR to curtail large negative outcomes. Park and Irwin (2007) point out that "… the riskiness of technical trading rules is often ignored in early studies…" and suggest that more attention should be directed to the analysis of TTR risk-return tradeoff. Further motivation comes from Moskowitz et al. (2012), who state that "… time series momentum may be a hedge for extreme events." Their findings suggest that tail risk may be mitigated by applying TTR. Moreover, Faber (2007) documents that momentum-based TTRs reduce investment risk by avoiding large drawdowns, whereas Marshall et al. (2007) show that

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

[2] 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 TTR superiority over a buy-and-hold (BH) strategy are Ang and Bekaert (2007), Brock et al. (1992), Marshall et al. (2017), Ni et al. (2015), Pesaran and Timmerman (1995), to name but a few.

TTRs they analyze are not particularly susceptible to crash risk. All of these papers allude to the possibility of TTR applications reducing investment left tail risk. In this paper, we formally test this.

To further highlight the importance of studying left tail risk, 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 portfolio's return falling below a minimum threshold is minimized. It has since long been recognized that investors' preferences over downside losses are different from those of upside gains (Ang et al., 2006). Gul (1991) describes preferences consistent with disappointment aversion that place greater weights on losses relative to gains in agents' utility functions. Further, we note that in the presence of margin calls (Brunnermeier & Pedersen, 2008) and limited risk bearing capacity (Siriwardane, 2019) large single losses have negative indirect effects.

The contribution of our paper lies in using TTR as a technique to reduce left tail risk in investment returns. Most TTR-studies focus on mean returns, whereas our interest is on the potential reduction of (extreme) risk. We thus take a new perspective that differentiates our study from the predominant type of TTR research. We find that in virtually all TTR specifications, all tail risk measures are significantly lower than those of a buy-and-hold strategy. In general, tail risk measures are reduced by about a third and remain very stable across various trading strategy specifications. From our cross-sectional analysis with single US stocks and international indices, we find that TTR are more beneficial when initial risk levels are high. TTR strategies also allow investors to avoid a significant percentage of large negative shocks. The percentage of avoided negative shocks is substantially higher in recessions – precisely when it is most valuable. We also document feedback effects between TTR and the business cycle. Specifically, we find that the frequency of TTR buy signals is a strong predictor of various stages of business cycle. Interestingly, tail risk reduction does not come at a cost of lower performance. Across our long sample period, Sharpe ratios are higher, maximum drawdowns lower, and worst years' returns higher than those corresponding to a buy-and-hold strategy.

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 follow Sullivan et al. (1999) reality check bootstrap approach and test whether the best model encountered has no superiority over the buy-and-hold. The results indicate that our findings are not a by-product of data snooping. Our findings are robust to inclusion of transaction costs and hold in 38 international markets.

Our strong and robust empirical results provide a new and yet understudied insight into the otherwise large and deep literature on TTR. Our paper stands out from most existing studies on technical trading rules in that our main focus is on avoidance of large negative returns, rather than profitability. The rest of the paper is organized as follows. Section 2 presents methodology and data. Section 3 describes the results. Section 4 discusses robustness of our findings. Section 5 concludes.

2. Methodology and Data

There is an extensive literature on TTR which apply a wide range of techniques to various asset categories. Park and Irwin (2007) provide a comprehensive survey of TTR studies in foreign exchange, commodity futures, and equity markets. These studies apply TTR in the form of generic algorithms, (non-linear) statistical models, and chart patterns. Most of these studies apply TTR to stock market indices – an approach similar to that of Brock et al. (1992). In their survey, Park and Irwin (2007) state that the paper by Brock et al. (1992) "… is one of the most influential works on technical trading rules among modern studies." Along the same line, Fang et al. (2014) rate the Brock et al. (1992) paper as "an important milestone in the field of technical analysis." Similar judgements regarding this paper can be found in Marshall et al. (2017), Sullivan et al. (1999), and Taylor (2014). Based on these statements, we also use the Brock et al. (1992) study as a benchmark for our approach. We use their choice of assets (stock markets), with the Dow Jones as basis. We use similar techniques, described in detail below. We do expand the data sample by extending the period, adding many new country-indices and by adding US individual stocks to the analysis. Taylor (2014) also studies TTR on DJIA individual stocks, but few other papers do so.

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).[3]

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 investment otherwise. The equity index return at time $t + 1$ is estimated by the following three time-series models: $AR_{M2}(1)$, $GARCH_{M2}(1,1)$, and $EGARCH_{M2}(1,1)$, 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 $AR_{M2}(1)$ models σ_t is constant. For the GARCH and EGARCH models σ_t takes the appropriate form.[4]

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 MA(M1,M2) signals with the $AR_{M2}(1)$ signal.[5]

2.2.Risk Measures

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

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[3] 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.

[4] See Bollerslev (1986) for the GARCH specification and see Nelson (1991) for the EGARCH specification. For the $AR_{M2}(1)$ strategy, we run the model for M2=100, 150, 200. To guarantee stability of the estimates we only run the GARCH and EGARCH for M2=200. In combination with the two thresholds values for *d*, this leads to 10 different time-series strategies.

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

$$Max\ drawdown = \max_{t=1,\dots,T}\left[\frac{\max_{i=1,\dots,t} p_i - p_t}{\max_{i=1,\dots,t} p_i}\right] \quad (2)$$

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

To further study tail behavior of the return distributions, we use Value-at-Risk (VaR) and Expected Shortfall (ES). These measures have a specific focus on the extremely negative realizations. Given the rare occurrence of these observations various frameworks have been developed to estimate VaR and ES. In the main results we use the non-parametric approach. In unreported results, we also estimate VaR and ES in a semi-parametric approach which relies on extreme value theory and assumes the return distribution is heavy tailed.[6] The non-parametric estimates provided are interchangeable with the semi-parametric approach.

The VaR is the quantile of the distribution at which a loss greater than VaR has probability p. Here p is typically chosen to be small, such that it reflects an extreme event. Take returns R_i in a sample of size n. Arrange the R_i observations in ascending order such that,

$$min(R_1, \dots, R_n) = R_{(1,n)} \leq R_{(2,n)} \leq, \dots, \leq R_{(n,n)} = max(R_1, \dots, R_n)$$

Here $R_{(1,n)}$ is the most negative observation out of a sample n. The non-parametric VaR measure is in this case

$$\text{VaR} = -R_{([np],n)}, \quad (3)$$

where $[np]$ is the integer part of np.

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:

$$ES = -\frac{1}{[np]}\sum_{j=1}^{[np]} R_{(j,n)} \quad (4)$$

These two measures are easy to implement and in an unconditional framework require little assumptions.

2.3. *Data*

[6] See Danielsson et al. (2006) for a detailed description of the extreme value theory methodology.

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, 2021.[7] We replicate the analysis on 38 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[8] and from the OECD data center for the other countries. The US business cycle data is obtained from the NBER. We rely on the OECD turning point dataset for other national business cycle data. Table 1 presents the detailed summary of data series used in sections 3.1 – 3.3 of this paper. Further, individual stock price data is obtained for the period of 1925-2020 from the Center for Research in Security Prices (CRSP). The CRSP database contains individual stock data from NYSE, AMEX, NASDAQ, and NYSE Arca. To create book-to-market ratios, we merge the CRSP data with the Compustat database. We restrict the sample to stocks with more than sixty months of data, average price above $5, less than twenty percent of zero-return days, and to common stocks with share codes 10 and 11. This leaves a total of 9,331 stocks for the analysis in section 3.4.

3. **Results**

3.1.Performance metrics

Figure 1 gives a visual representation of the performance of the TTR relative to a passive buy-and-hold (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(1,150) trading signals you would be better off than the BH strategy.[9] The trading rule frequently avoids drops of 4% or more 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 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 2. The results are quite striking. In all MA specifications, Sharpe ratios are significantly higher, maximum drawdowns lower, and worst years' returns higher

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[7] We acknowledge that the stock index itself is non-tradable. Huang and Huang (2020) show that MA strategies become less profitable when they are implemented using ETFs rather than their underlying index. For the focus of our paper, i.e., the reduction of tail risk, we feel that using a stock index is representative, and our tail risk results in section 3 are strong. Moreover, they are in line with the nuanced picture painted by Huang and Huang (2020), who document higher CAPM alpha and appraisal ratios.

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

[9] The BH strategy results in $1,188.42 at the end of 2021, as compared to $4,199.91 for the MA(1,150) strategy.

than those corresponding to a BH strategy. We note that Huang and Huang (2020), using directly comparable MA strategies, report lower returns and Sharpe ratios compared to a BH strategy. However, their sample period starts substantially later and ends earlier than ours. Unreported results show that if we use their sample period, our results are very similar. The findings in our paper thus partly replicate and partly differ from theirs. We feel this enhances the strength of both studies and adds new insights to the use of MA strategies. Finally, 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 strategy's utility levels.

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.[10] For instance, a MA(1,50) strategy has a 2.5% VaR of 1.39%, as opposed to 2.17% 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 2.12% for a MA(1,50) strategy to 2.26% for a MA(5,150) strategy. This is substantially lower than the 3.32% expected shortfall of a BH strategy.

The results for time-series strategies are presented in Table 3. The results are largely consistent with those presented in Table 2. 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 4. 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

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[10] The numbers in brackets below the estimates in Table 2 are the bootstrapped one-sided p-values.

strategies simultaneously and unanimously yield a buy or sell signal. Thus, it may be intuitive to expect a mixed strategy's results to be superior to those of individual strategies. Our results, however, do not support this assertion.

Our main results are obtained using the DJIA full sample. We also replicate the analysis on sub-samples of DJIA data. The results are presented in Table 5. Our findings are robust. The Sharpe ratios of the AR(100) and AR(200) in the sub-period 1896-1927 are the only two that have a lower performance than the BH strategy. For the 1990-2021 sub-sample the Sharpe ratio performance is mixed for all three types of strategies. This is in line with the findings by Fang et al. (2014). However, when it comes to the risk measures, they are uniformly lowered in all subsamples.

3.2.Avoiding largest losses

One of the most desirable trading strategy outcomes is avoidance of large losses. Panel (a) of Table 6 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.[11] Table 6 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. Other than for negative 1.0% shocks in the 1990-2021 sub-sample, 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 1990-2021 sub-period.

3.3.TTR and the Business Cycle

Avoiding large losses is valuable but avoiding them in time of a recession is more valuable still. Panel (b) of Table 6 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

[11] In unreported results, we perform the analysis for all the trading strategies and find little variation between the strategies. The one exception is the TTR with the GARCH model specification. Given that the EGARCH TTR is at par with the reported results, the asymmetric persistence of large negative shocks is important for the TTR.

[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.

more strikingly, all shocks of -2.5% or greater are avoided in the most recent 1990-2021 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 likely already taken a tumble. The TTR strategies use the stock market's 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 refer to Ilmanen (2011) Ch. 16, who relates asset returns to the 'pure fundamentals' in the economy, thus (changing views on) GDP and CPI. We refer also to Sander (2018), who models return predictability to switch across the business cycle, where stocks are predictable only in recessions. Along the same line, Tsiakas et al. (2020) find that stock return predictability concentrates in bad times. Finally, using a Bayesian nonparametric approach, Yang (2019) shows that lagged stock returns significantly predict economic growth, and in a time-varying manner. 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.

To investigate this link further, we use logit regressions to predict the different stages of the economic cycle with the signals that are produced by the TTR rules. We divide the booms into three equally spaced stages: early, mid, and late boom, and recession periods up in two equal parts, early and late recession. We use the average signal by a TTR over the previous month as the regressor, resulting in

$$Stage_{t+1} = c + \beta \cdot TTR_t + e_{t+1} \tag{5}$$

Here $Stage_{t+1}$ takes on value 1 if at time t+1 the economy is in the relevant stage of the business cycle. If the TTR predict the real economy we expect it to signal to get out of the market if a recession is coming at t+1, resulting in a negative β coefficient. Therefore, we expect a positive coefficient in case the regression is estimated on the boom cycles.

The significant negative beta coefficient in Table 8 shows that the TTR is relatively low before an early crisis period. The same is true for a late crisis period. One should further notice that the coefficient on the late crisis is smaller. For the boom periods the coefficients are positive and significant, except for the late boom. For most strategies there is a relatively strong relationship in the early stages of the business cycle and during the trailing periods the relationship becomes weaker.[13]

3.4. TTR and Individual Stocks

We believe our empirical results in the previous section are robust and convincing at index level. However, an index, by the virtue of diversification, is a relatively stable asset. The next logical step is to test TTR strategies in an asset class where left tail risk is arguably more important than it is in an index – individual stocks.[14] Therefore, we investigate to what extent do investment returns in different stocks (classified, e.g., by size) benefit from application of technical trading rules. To better understand tail risk reduction capacity of the TTR we use the rich cross-section of US individual stocks that is described in section 2.3.

We measure the risk reduction capacity of the TTR as the difference between the risk measure with randomly assigned ‘out’ signals (benchmark), where the number of ‘out’ signals equals that of the TTR, and the actual risk measure of the TTR itself.[15] We introduce the risk reduction measure to assess if TTR-signals actually reduce investment risk more than purely randomly generated sell-signals. We note that all ‘out’-signals reduce tail risk, because of closing the position and reverting to cash. As a result, the more out-signals occur, the more tail risk is reduced, by construct. We deem it more relevant to measure if TTR reduce risk over and above a strategy in which the same number of randomly generated signals are followed. This assessment allows us to answer the question whether TTR-signals actually tend to reduce the investment risk at the right moment in time.

[13] In Table 9 we reversed the variables for reverse causality and find no significant relationships in predicting the TTR with the business cycle stages.
[14] We would like to thank an anonymous referee for this valuable suggestion.
[15] Replacing risk measure RM(random) with risk measure RM(BH) yields similar results.

$$Risk\ reduction_i = 1/100 \sum_{s=1}^{100} RM_i^s(random) - RM_i^{TTR} \qquad (6)$$

The benchmark risk measure for stock i with randomly generated signals, $RM_i(random)$, is averaged over 100 repeated draws to limit noise in cross-sectional regression. As an example, take the case of stock EBIX COM INC (permno 11481). The 2.5% VaR of MA(1,150) strategy is 5.68%. The TTR puts funds in the risk-free rate 3,581 out of 7,612 available days. We therefore pick 3,581 random days that the funds are invested in the risk-free rate and calculate the 2.5% VaR. The process is repeated 100 times and the average VaR is computed. The average 2.5% VaR from random 'out' signals is 7.43%, leading to a TTR risk reduction of 1.75% (calculated as 7.43% - 5.68%). We repeat this process for each stock in the sample.

The left panel of Figure 2 displays the scatterplot of the percentage of 'out' signals versus the initial risk level, as measured by buy-and-hold 2.5% VaR. We can see that the more risky the stock, the more often the TTR produces an out signal.[16] The right panel shows that 91.1% of stocks experience a positive risk reduction after applying the MA(1,150) strategy. Application of the TTR generates signals that outperform those that are generated randomly. Further, the fact that the finding does not hold for the full hundred percent of the stocks in the sample, suggests that there is some level of heterogeneity across firms in their TTR risk reduction capacity.

Next, we use the initial level of tail risk (RM(BH) – risk measure of a buy-and-hold), and stock characteristics commonly used in asset pricing research (see e.g., Ang et al, 2006), average log of market capitalization, average book-to-market ratio, and average turnover as independent variables in a cross-sectional regression.

$$Risk\ reduction_i = c + \beta_1 RM_i(BH) + \beta_2 Bk\text{-}Mkt_i + \beta_3 log(Size_i) + \beta_4 Turnover_i + e_i \qquad (7)$$

Table 10 presents the results for MA(1,150), MA(5,150), AR(100), AR(200), Mix(1,150), and Mix(5,150) strategies for the 2.5% VaR risk measure.[17]

The positive and significant coefficient for the initial risk level shows that riskier stocks have the most to gain from using TTR.[18] Turnover is significant and negatively related to risk

[16] This outcome is what has partially motivated our use of a 'random' benchmark. After all, the best way to eliminate tail risk is to invest in a risk-free rate 100% of the time.
[17] The results for other TTR and different VaR and ES measures are similar and are available upon request. Additional unreported evidence indicates that the average Sharpe ratio increases significantly by 0.05 relative to the "random" benchmark.
[18] The results are consistent when volatility, rather than VaR, is used as an initial risk measure. Results are available from the corresponding author upon request.

reduction. Stocks with lower turnover might exhibit greater deviations from fundamental values and thus benefit more from TTR application. Book-to-market ratio is also negatively related to risk reduction, implying that growth stocks have more to gain from TTR.

We document a positive relationship between log of firm size and risk reduction. Intuitively, one would expect smaller firms to have most to gain from TTR application, as these firms tend to be riskier – Amaya et al. (2015) provide evidence of a negative relationship between size and volatility. However, the relationship is not universal. Lo et al. (2002) report inconclusive results regarding the effect of size on TTR effectiveness. Campbell et al. (2002) point out that individual stocks have become more volatile relative to market volatility, and the correlations between individual stocks have declined. The findings suggest that the relationship between firm size and volatility may be transitory. We also note that the random benchmark we use in risk reduction assessment ensures a more fair assessment of the relative success of the TTR compared to using a buy-and-hold benchmark. Larger stocks tend to produce fewer 'out' signals than smaller ones. Risk reduction will always occur when substituting returns for risk-free rate. The 'random' benchmark ensures that timing is the decisive component in risk reduction, as opposed to simply the fraction of 'out' signals, which is highly correlated to volatility. [19]

3.5. International Markets

To study the adaptability of the trading rules to different markets we analyse their performance on 38 national indexes. Table 11 reports the findings. Our results are robust. Even though Sharpe ratios do not outperform the buy-and-hold strategy for every specification,[20] tail risk measures are almost always better than those of a passive strategy. Maximum drawdown is lower in all strategy specifications in 37 out of 38 markets. Worst year performance is better in all specifications in 36 markets, and so is the expected shortfall. Value-at-risk measures are lower in all 38 markets in all specifications.

Table 12 reports percentage of avoided shocks across different national indices, following the format of Table 6. We report the results for the whole sample, as well as during (local)

[19] Our methodology could be challenged due to the fact that regression equation above uses average stock characteristics computed over the entire sample period. However, stock characteristics may change substantially over time, and so can the potential for risk reduction from TTR application. To address this potential issue, we split the sample in separate decades, compute stock characteristics, e.g., for 1980s, 1990s, etc. and use them in a pooled regression. We find that the unpublished results remain robust. They are available upon request.

[20] Sharpe ratios are higher in all specifications for 24 out of 38 markets. In the remaining 14 markets, outperformance depends on strategy specification.

recessions for all 38 international indices.[21] 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 6 out of 38 countries are we able to avoid more than 50% of shocks of a magnitude of -0.5% or lower. The number increases to 22 out of 38 for shocks of -1.0% or lower, and to 30 out of 38 for shocks of -1.5% or lower. The only consistent exception is China, where the percentage of avoided shocks tends to stay below 50%. Overall, our evidence is consistent with the results reported in Table 6 – following a TTR strategy will result in avoidance of a high percentage of negative shocks, with that percentage being higher in recessions. This result holds for the different TTR strategies.

We now investigate which countries' indices benefit the most from TTR application. We employ widely used measures of financial market development – depth and efficiency (see Cihak et al, 2012).[22] We estimate the following regression:

$$Risk\ reduction_i = c + \beta_1 RM_i(BH) + \beta_2 Efficiency_i + \beta_3 Depth_i + e_i \qquad (8)$$

The results are presented in Table 13. Initial risk level, as measured by buy-and-hold 2.5% VaR is significantly and positively related to risk reduction, i.e., riskier indices have most to gain from TTR application. Efficiency (as measured by turnover) is negatively related to risk reduction. Both of these results are in line with our findings for individual stocks. Stock market depth is not significantly related to risk reduction.

4. Discussion and Robustness

4.1.Reality check bootstrap

Table 14 reports the results of the reality check bootstrap, which addresses the issue of data snooping and tests whether the best model encountered has no superiority over the benchmark model (BH). We see that for VaR and ES the most reactive simple moving average strategy

[21] 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 analysis. Qualitatively the results are very similar.

[22] Stock market turnover ratio proxies efficiency. Depth is measured by stock market capitalization to GDP ratio. The "access" variable (market capitalization excluding top 10 companies to total market capitalization ratio) is missing for seven countries and is, therefore, excluded. Including the access variable shows a negative relationship with risk reduction.

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.[23] 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.

4.2. 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. Table 15 - Table 17 report the results similar to those reported in Table 2 -Table 4, while adding a 0.15% transaction cost per individual buy or sell transaction.[24] The results for the moving average strategy (Table 15) are virtually identical to the ones reported in Table 2, suggesting that transaction costs play only a small part in explaining the results. The results for the time-series strategies, reported in Table 16, are more sobering. While the tail risk measures are only marginally higher than those reported in Table 3, 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 AR(100) strategy, it is below the BH). However, once d is set to 0.1, automatically reducing the number of transactions, Sharpe ratios increase substantially. Mixed strategy results (Table 17) 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.

4.3. 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

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[23] VaR and ES always stand to benefit from random sell signals. Therefore, we use an alternative bootstrapped benchmark with randomly allocated sell signals to the BH strategy to get the standard errors for VaR and ES (see Appendix A for a description). Furthermore, given the clear outperformance of all strategies a further reparameterization of the TTR are unlikely to alter this result. This point is also argued by Sullivan et al. (1999).

[24] Many discount brokers offer a fixed $ transaction fee for trading in equities. Assuming that the initial investment is sizable, these costs 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.

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 counterintuitive 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 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. (2020); 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 results 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.

5. Conclusion

Technical trading rules-based strategies in equity markets substantially reduce left tail risk exposure. 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 the real economy. Theory suggests that risk reduction should be accompanied by a performance penalty. Our findings, however, are not consistent with this notion – TTR performance measures are almost always better than those corresponding to a buy-and-hold strategy. 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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6. **Appendix.**

A. White's reality check bootstrap

Here we elaborate on the reality check bootstrap procedure developed by White (2000). Take metric M_k for strategy k,

$$M_k = g(R_{t,k})$$

Here g is a function that transforms $R_{t,k}$ excess returns, in excess of the risk-free rate, generated by the trading strategy into a metric like expected return or Value-at-Risk. The trading strategy returns,

$$R_{t,k} = y_{t+1} S_{t,k}(\chi_t, \beta_k),$$

are produced by the signal $S_{t,k}(\chi_t, \beta_k)$. The signals, in our case take on value $\{0,1\}$. The series χ_t is the data used to arrive at the signal and β_k is the parameter vector in the model to arrive at signal $S_{t,k}$. In case of the MA rules there are no parameters to be estimated. This is only relevant for the time-series models. To test the performance of the trading strategy, we benchmark the returns against a buy-and-hold strategy. The performance statistic,

$$f_k = g(R_{t,k}) - g(R_{t,0})$$

assesses the over performance of the trading returns over the benchmark strategy based on metric *M*. Here S_0 are the trading signal for the benchmark strategy.

The reality check bootstrap tests whether the best technical trading rule is no better than the performance of the benchmark. In other words,

$$H_0\colon \max_{k=1,\ldots,l}\{E(f_k)\} \leq 0$$

To test the null hypothesis we bootstrap null distribution. We resample the returns $R_{t,k}$. Due to the nature of the data and that the trading strategies rely on the time-series properties underlying the financial data, we use a block bootstrap procedure. The block sizes are randomly drawn from a geometric distribution with mean two. The results are robust to larger values for the mean.

As prescribed by White (2000), resampling the returns from the trading rules yields B bootstrapped values of f_k, denoted as $f_{k,i}^*$. We set *B*=500 and then construct the following statistics:

$$\overline{V_l} = \max_{k=1,\ldots,l}\left\{\sqrt{n}(f_k)\right\}$$

and

$$\overline{V_{l,i}} = \max_{k=1,\ldots,l}\left\{\sqrt{n}\left(f_{k,i}^* - f_k\right)\right\}$$

Here $\overline{V_{l,i}}$ provides the distribution under the null. We test whether $\overline{V_l}$ falls outside the empirical confidence interval of empirical null distribution. To provide standard errors for the performance metric of a single strategy, we set *l* to one. (White, 2000)

Reality bootstrap for downside risk measures

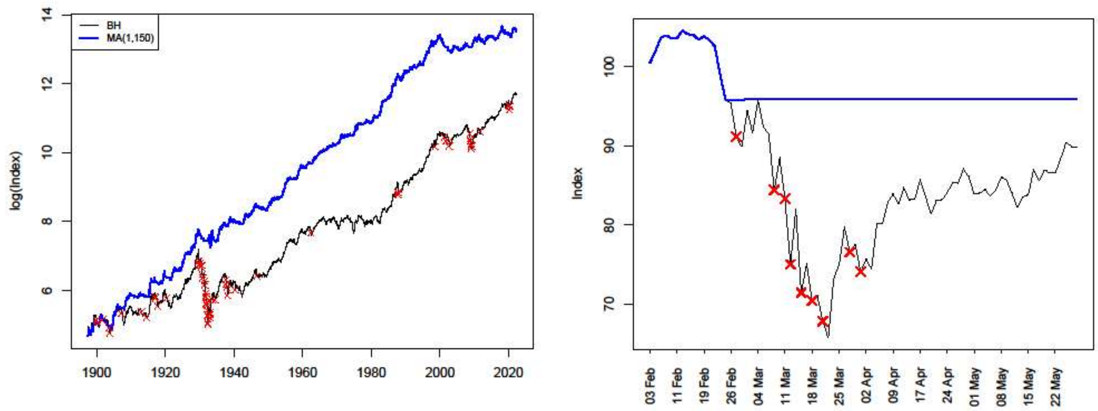
Risk metrics like Value-at-Risk and Expected shortfall focus on one side of the return distribution. The nature of the in-and-out trading strategy is that some of the negative returns inherently are avoided. A strategy with random signals improves the one-sided risk metrics over the buy-and-hold strategy. For symmetric risk measures this does not cause any issues, however, for one-sided risk measures like VaR and Expected Shortfall, this is an unfair benchmark. In this respect the benchmark at most performs as well as the trading strategy. Therefore, we introduce for the one-sided risk metrics a new benchmark. Take $O_k = \sum_t 1 - S_k^t$, as the number of times the technical trading strategy is out. We randomly assign O_k signals to the benchmark. Therefore giving,

$$f_k = g\left(y_{t+1}S_{t,k}(\chi_t, \beta_k)\right) - g\left(y_{t+1}S_{t,0}(\chi_t, \beta_0, O_k)\right)$$

where $S_{t,0}$ a series of signals with O_k randomly allocated out signals. We repeat the block-bootstrap procedure to get the null distribution for the one-sided risk metrics.

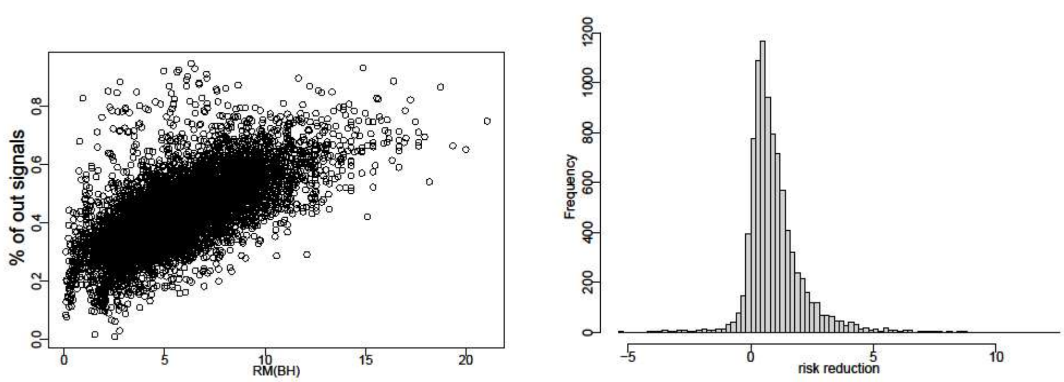
B. Figures

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



These figures show the performance of a BH strategy (thin black line) and the TTR MA(1,150) rule (thick blue line) for the DJIA. The ability of the TTR rule to avoid large negative returns is also highlighted in these figures. The red crosses are negative daily returns of 4% or more in a BH strategy which are avoided by the TTR strategy implementation. The left displays the whole sample period from 1896 till 2020. The right figure zooms in on the Covid-19 crisis showcasing an investment of 100 on 01-02-2020.

Figure 2: Descriptive statistics single stocks



This figure shows characteristics of US individual stock's 2.5% VaR when TTR is applied to the time-series provided in the CRSP database. Panel (a) of this figure displays a scatter plot of the percentage of sell signals, from MA(1,150), versus the initial level of the risk measure. Panel (b) provides the distribution of risk reduction measured as the difference between our benchmark – randomly assigned sell signals – and the TTR strategy. We use a total of 9,331 single stock time series.

C. Tables

Table 1: Data summary

Name	Data Source	Start	End
Australia Equity Index	WRDS world Index	1986-07	2021-12
Austria Equity Index	WRDS world Index	1999-07	2021-12
Belgium Equity Index	WRDS world Index	1999-07	2021-12
Brazil Equity Index	WRDS world Index	1995-07	2021-12
Chile Equity Index	WRDS world Index	2002-02	2021-12
China Equity Index	WRDS world Index	1994-07	2021-12
Colombia Equity Index	WRDS world Index	2005-07	2021-12
Denmark Equity Index	WRDS world Index	1986-07	2021-12
Egypt Equity Index	WRDS world Index	2000-01	2018-04
Finland Equity Index	WRDS world Index	1999-07	2021-12
France Equity Index	WRDS world Index	1999-07	2021-12
Germany Equity Index	WRDS world Index	1999-07	2021-12
Greece Equity Index	WRDS world Index	2001-07	2021-12
Hong Kong Equity Index	WRDS world Index	1986-07	2021-12
Hungary Equity Index	WRDS world Index	1996-07	2021-12
India Equity Index	WRDS world Index	1993-07	2021-12
Indonesia Equity Index	WRDS world Index	1990-07	2021-12
Ireland Equity Index	WRDS world Index	1999-07	2021-12
Italy Equity Index	WRDS world Index	1999-07	2021-12
Japan Equity Index	WRDS world Index	1986-07	2021-12
Malaysia Equity Index	WRDS world Index	1989-07	2021-12
Mexico Equity Index	WRDS world Index	1993-07	2021-12
Netherlands Equity Index	WRDS world Index	1999-07	2021-12
New Zealand Equity Index	WRDS world Index	1991-07	2021-12
Norway Equity Index	WRDS world Index	1988-07	2021-12
Philippines Equity Index	WRDS world Index	1992-07	2021-12
Poland Equity Index	WRDS world Index	1995-07	2021-12
Portugal Equity Index	WRDS world Index	1999-07	2021-12
Singapore Equity Index	WRDS world Index	1986-07	2021-12
Spain Equity Index	WRDS world Index	1999-07	2021-12
Sweden Equity Index	WRDS world Index	1986-07	2021-12
Switzerland Equity Index	WRDS world Index	1986-07	2021-12
Taiwan Equity Index	WRDS world Index	1988-07	2021-12
Thailand Equity Index	WRDS world Index	1988-07	2021-12
Turkey Equity Index	WRDS world Index	2006-02	2021-12
South Africa Equity Index	WRDS world Index	2002-06	2021-12
South Korea Equity Index	WRDS world Index	1988-07	2021-12
United Kingdom Equity Index	WRDS world Index	1986-07	2021-12
Dow jones industrial average	Measuring Worth (w)	1896-10	2022-04
One-month Treasury bill rate	Kenneth R. French library (w)	1926-07	2021-12
International short term interest rates	OECD Data (w)	1956-01	2021-12
International Turning Points Data	OECD Data (w)	1947-02	2021-12
Individual US stock data	WRDS CRSP database	1925-01	2020-12

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 2: 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%
E[R]	0.07	0.08	0.08	0.07	0.07	0.07	0.07	0.08	0.08	0.07	0.07
	-	(0.18)	(0.12)	(0.3)	(0.27)	(0.49)	(0.48)	(0.2)	(0.2)	(0.29)	(0.25)
SR	0.26	0.53	0.51	0.45	0.44	0.41	0.40	0.48	0.48	0.45	0.44
	-	(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%	2.17	1.39	1.39	1.45	1.45	1.47	1.47	1.47	1.46	1.47	1.47
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 1.0%	3.10	2.00	2.00	2.08	2.08	2.11	2.12	2.09	2.09	2.10	2.10
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 0.05%	4.01	2.47	2.47	2.54	2.54	2.59	2.60	2.60	2.60	2.61	2.62
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 2.5%	3.32	2.12	2.13	2.21	2.21	2.25	2.26	2.23	2.23	2.25	2.25
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 1.0%	4.49	2.86	2.87	2.96	2.97	3.01	3.03	3.00	3.00	3.02	3.02
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 0.5%	5.50	3.53	3.53	3.66	3.66	3.72	3.75	3.70	3.70	3.74	3.74
	-	(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, 2021.

Table 3: 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%
E[R]	0.07	0.08	0.08	0.09	0.08	0.09	0.08	0.10	0.09	0.10	0.08
	-	(0.11)	(0.09)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
SR	0.26	0.50	0.48	0.59	0.51	0.60	0.50	0.62	0.47	0.62	0.45
	-	(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)	(0.05)	(0)	(0)	(0)	(0)	(0.14)	(0.05)	(0.68)	(0.39)
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)	(0.14)	(0.05)
VaR 2.5%	2.17	1.54	1.54	1.54	1.52	1.57	1.57	1.68	1.74	1.51	1.55
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 1.0%	3.10	2.21	2.21	2.20	2.22	2.26	2.26	2.43	2.52	2.24	2.25
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 0.05%	4.01	2.81	2.76	2.76	2.88	2.95	2.98	3.18	3.22	2.99	3.00
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 2.5%	3.32	2.39	2.38	2.38	2.41	2.47	2.48	2.68	2.76	2.46	2.51
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 1.0%	4.49	3.26	3.23	3.24	3.32	3.38	3.39	3.71	3.80	3.45	3.51
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 0.5%	5.50	4.06	4.03	4.04	4.16	4.22	4.24	4.64	4.76	4.36	4.45
	-	(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, 2021.

Table 4: 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%
E[R]	0.07	0.07	0.07	0.07	0.08	0.07	0.08	0.08	0.07	0.08	0.07
	-	(0.25)	(0.21)	(0.25)	(0.35)	(0.32)	(0.51)	(0.14)	(0.05)	(0.2)	(0.1)
SR	0.26	0.49	0.46	0.47	0.50	0.44	0.49	0.50	0.44	0.48	0.42
	-	(0)	(0)	(0)	(0.01)	(0)	(0.03)	(0)	(0)	(0)	(0)
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%	2.17	1.40	1.45	1.47	1.46	1.48	1.48	1.48	1.49	1.48	1.50
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 1.0%	3.10	2.01	2.05	2.12	2.12	2.12	2.13	2.10	2.15	2.12	2.16
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 0.05%	4.01	2.48	2.54	2.62	2.62	2.62	2.64	2.62	2.72	2.63	2.72
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 2.5%	3.32	2.15	2.20	2.25	2.25	2.27	2.27	2.24	2.33	2.26	2.33
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 1.0%	4.49	2.90	2.95	3.03	3.04	3.04	3.06	3.01	3.17	3.04	3.17
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 0.5%	5.50	3.59	3.65	3.73	3.74	3.74	3.77	3.71	3.97	3.75	3.97
	-	(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, 2021.

Table 5: Sub-samples of the DJIA index

	SR	MDD	Worst year	VaR 2.5%	VaR 1.0%	VaR 0.5%	ES 2.5%	ES 1.0%	ES 0.5%
1896-1927	Some	All	All	All	All	All	All	All	All
1927-1963	All	All	All	All	All	All	All	All	All
1963-1990	All	All	All	All	All	All	All	All	All
1990-2021	Some	All	All	All	All	All	All	All	All

This table presents strategy performance comparison across different subsamples of the DJIA index. For the subsample we run all the specification for the MA, time-series and mixed strategies. For each performance metric we summarize whether all strategies outperformed the buy-and-hold strategy. “All” means that all strategy specifications outperform a buy-and-hold. “Some” indicates that at least once the BH is not outperformed.

Table 6: Large negative shocks of DJIA

	1896-2021		1896-1927		1927-1963		1963-1990		1990-2021	
Shock	% out	Shocks	% out	Shocks	% out	Shocks	% out	Shocks	% out	Shocks
-0.5 %	44	7851	49	2154	47	2210	48	1578	35	1804
-1 %	52	3795	55	1032	56	1149	51	649	46	911
-1.5 %	59	1879	62	486	62	639	55	256	53	476
-2 %	64	1024	61	256	67	409	64	94	62	258
-2.5 %	70	582	65	130	72	274	72	39	73	134
-3 %	70	368	59	71	73	192	65	20	75	83
-3.5 %	74	253	61	44	73	139	62	13	86	57
-4 %	75	173	62	26	73	97	62	8	88	42

(a) All negative shocks

	1896-2021		1896-1927		1927-1963		1963-1990		1990-2021	
Shock	% out	Shocks	% out	Shocks	% out	Shocks	% out	Shocks	% out	Shocks
-0.5 %	74	2275	70	891	76	767	76	325	82	245
-1 %	80	1322	80	428	81	514	77	174	88	173
-1.5 %	84	764	84	199	83	345	85	86	91	118
-2 %	87	472	90	102	84	252	87	38	93	75
-2.5 %	88	308	94	50	84	186	88	16	100	53
-3 %	88	210	92	24	84	140	75	4	100	40
-3.5 %	90	153	93	15	86	103	50	2	100	33
-4 %	90	108	100	7	85	73		0	100	28

(b) Negative shocks in NBER recessions

This table reports the percentage of negative shocks which are avoided due to the trading strategy. In this table we utilize the 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. Panel (a) collects the shocks over the whole sample. Panel (b) only collects the shocks in the recessions of the sample stated in the column.

Table 7: Large positive shocks of DJIA

	1896-2021		1896-1927		1927-1963		1963-1990		1990-2021	
Shock	% out	Shocks	% out	Shocks	% out	Shocks	% out	Shocks	% out	Shocks
-0.5 %	41	8939	43	2472	43	2530	41	1656	36	2143
-1 %	49	3983	48	1094	53	1121	45	724	49	1011
-1.5 %	59	1809	59	449	61	581	49	312	64	458
-2 %	67	912	65	198	68	332	55	148	75	230
-2.5 %	75	506	74	103	70	212	70	66	87	123
-3 %	79	313	81	52	72	151	77	35	95	74
-3.5 %	81	205	88	25	72	110	82	22	100	48
-4 %	82	138	92	12	72	80	83	12	100	34

(a) All positive shocks

	1896-2021		1896-1927		1927-1963		1963-1990		1990-2021	
Shock	% out	Shocks	% out	Shocks	% out	Shocks	% out	Shocks	% out	Shocks
-0.5 %	69	2216	68	884	72	743	66	293	83	235
-1 %	78	1172	75	388	82	421	67	183	86	166
-1.5 %	84	664	86	173	85	280	73	94	88	114
-2 %	87	409	88	77	88	192	75	57	91	81
-2.5 %	88	270	96	45	86	138	77	30	93	55
-3 %	88	185	95	21	84	107	78	18	97	38
-3.5 %	87	132	100	12	84	80	69	13	100	27
-4 %	88	95	100	4	85	62	71	7	100	22

(b) Positive shocks in NBER recessions

This table reports the percentage of positive shocks which are avoided due to the trading strategy. In this table we utilize the 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 8: Logit regression predicting business cycles stages

	Early Crisis		Late Crisis		Early Boom		Mid Boom		Late Boom	
	Coeff	t-stat.	Coeff	t-stat.	Coeff	t-stat.	Coeff	t-stat.	Coeff	t-stat
MA(1,50)	-1.86	-8.88	-0.54	-2.39	0.87	5.44	0.44	2.80	0.06	0.41
MA(1,150)	-2.42	-11.90	-1.41	-6.90	1.06	6.95	0.67	4.54	0.50	3.38
MA(5,150)	-2.37	-11.83	-1.40	-6.90	1.04	6.91	0.65	4.46	0.50	3.43
MA(1,200)	-2.57	-12.64	-1.59	-7.84	1.17	7.59	0.70	4.76	0.60	4.04
MA(5,200)	-2.52	-12.58	-1.58	-7.86	1.15	7.52	0.68	4.65	0.62	4.19
AR_{200}	-3.29	-12.26	-2.53	-8.92	1.37	6.72	1.21	5.90	0.80	3.98
$Garch_{200}$	-2.86	-11.06	-2.62	-9.13	1.57	6.75	1.33	5.72	0.66	2.99
$EGarch_{200}$	-2.40	-9.09	-2.42	-7.99	0.75	3.81	1.41	6.64	0.48	2.40
MMA(1,50)	-2.15	-10.55	-1.09	-5.12	1.12	7.00	0.65	4.18	0.13	0.84
MMA(1,150)	-2.05	-10.29	-0.93	-4.34	1.01	6.23	0.67	4.22	0.12	0.78
MMA(5,150)	-2.05	-10.29	-0.93	-4.34	1.01	6.23	0.67	4.22	0.12	0.78

The table presents the analysis of the information contained in the signals created by the TTR in predicting the different business cycle stages. The regression equation we estimate is $I(Stage)_{t+1} = c + \beta \cdot TTR_t + e_{t+1}$. Here $I(Stage)_{t+1}$ take on value 1 when the business cycle indicated in the column name occurs at time t+1 and zero otherwise. The TTR_t is the average of the TTR signals within month t. The particular TTR strategy is indicated in the first column. The equation is estimated with a logit model. The 5 different business cycle stages are created by equally dividing the NBER recessions in two periods and the boom periods in 3 equal parts. This analysis is done for the DJIA index over the whole sample period.

Table 9: Predicting TTR with business cycles

	Early Crisis		Late Crisis		Early Boom		Mid Boom		Late Boom	
	Coeff	t-stat.	Coeff	t-stat.	Coeff	t-stat.	Coeff	t-stat.	Coeff	t-stat.
MA(1,50)	-0.00	-0.16	-0.04	-1.72	-0.03	-1.04	0.04	1.76	0.03	1.11
MA(1,150)	0.01	0.38	-0.01	-0.44	-0.01	-0.47	-0.00	-0.08	0.02	0.61
MA(5,150)	0.01	0.29	-0.01	-0.45	-0.01	-0.42	-0.00	-0.06	0.02	0.63
MA(1,200)	0.02	0.58	-0.02	-0.71	-0.02	-0.62	-0.01	-0.19	0.03	0.92
MA(5,200)	0.01	0.50	-0.02	-0.65	-0.01	-0.44	-0.01	-0.33	0.03	0.91
AR_{200}	0.00	0.06	-0.01	-0.47	-0.00	-0.12	0.00	0.13	0.01	0.39
$Garch_{200}$	0.01	0.68	-0.01	-0.39	-0.01	-0.53	-0.00	-0.06	0.01	0.29
$EGarch_{200}$	0.01	0.30	0.01	0.54	-0.01	-0.29	-0.01	-0.71	0.00	0.16
MMA(1,50)	0.01	0.20	-0.04	-1.51	-0.02	-0.93	0.03	1.34	0.02	0.86
MMA(1,150)	0.02	0.71	-0.04	-1.63	-0.04	-1.37	0.03	1.20	0.03	1.05
MMA(5,150)	0.02	0.71	-0.04	-1.63	-0.04	-1.37	0.03	1.20	0.03	1.05

The table presents the analysis on whether the business cycle stage predicts the TTR signals. The regression equation we estimate is $TTR_{t+1} = c + \beta \cdot I(Stage)_t + e_{t+1}$. Here $I(Stage)_t$ take on value 1 when the business cycle indicated in the column name occurs at time t+1 and zero otherwise. The TTR_{t+1} is the average of the TTR signals within month t+1. The particular TTR strategy is indicated in the first column. The equation is estimated with a logit model. The 5 different business cycle stages are created by equally dividing the NBER recessions in two periods and the boom periods in 3 equal parts. This analysis is done for the DJIA index over the whole sample period.

Table 10: Cross-sectional regression for individual stocks

	MA(1,150)	MA(5,150)	AR(100)	AR(200)	Mix(1,150)	Mix(5,150)
VaR 2.5	0.13	0.14	0.08	0.09	0.14	0.15
	[48.65]***	[54.23]***	[43.65]***	[43.57]***	[52.83]***	[55.33]***
log(Size)	0.08	0.07	0.01	0.01	0.07	0.06
	[19.57]***	[16.82]***	[4.47]***	[2.18]**	[16.07]***	[15.51]***
Bk-Mkt	-0.01	-0.01	0	0	-0.01	-0.01
	[-3.54]***	[-3.47]***	[-1.63]	[-1.77]*	[-3.26]***	[-3.21]***
Turnover	-2.62	-4.07	-4.19	-4.91	-3.94	-4.32
	[-4.19]***	[-6.63]***	[-9.24]***	[-9.67]***	[-6.35]***	[-7.00]***
Constant	-1.91	-1.69	-0.34	-0.23	-1.63	-1.60
	[-20.72]***	[-18.68]***	[-5.04]***	[-3.06]***	[-17.81]***	[-17.63]***
R-squared	0.26	0.30	0.23	0.24	0.29	0.31

This table presents the coefficient estimates of regressing the measured risk reduction per stocks on stock characteristics and the initial level of risk. Log(size) is the log of the market capitalization of the firm. The book-to-market ratio (Bkt-Mkt) is book value of the firm over the market capitalization. The stock characteristics are measured as the average over the stock's sample period. The first row indicates for which TTR risk reduction is measured. T-statistics for the regression coefficients are given in parentheses, where the stars indicate 10%, 5%, or 1% significance level. The data is from the CRSP database.

Table 11: Strategy comparison across countries

	SR	MDD	Worst year	VaR 2.5%	VaR 1.0%	VaR 0.5%	ES 2.5%	ES 1.0%	ES 0.5%
Australia	All	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
Brazil	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	Some	All	All	All	All	All	All	All	All
Denmark	All	All	All	All	All	All	All	All	All
Egypt	All	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
Germany	Some	All	All	All	All	All	All	All	All
Greece	All	All	All	All	All	All	All	All	Some
Hong Kong	Some	All	All	All	All	All	All	All	All
Hungary	Some	All	All	All	All	All	All	All	All
India	All	All	All	All	All	All	All	All	All
Indonesia	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
Malaysia	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
New Zealand	Some	All	All	All	All	All	All	All	All
Norway	All	All	All	All	All	All	All	All	All
Philippines	All	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
Singapore	All	All	All	All	All	All	All	All	All
South Africa	Some	All	Some	All	All	All	All	All	All
South Korea	All	All	All	All	All	All	All	All	All
Spain	Some	All	All	All	All	All	All	All	All
Sweden	All	All	All	All	All	All	All	All	All
Switzerland	All	All	All	All	All	All	All	All	All
Taiwan	All	All	All	All	All	All	All	All	All
Thailand	All	All	All	All	All	All	All	All	All
Turkey	Some	All	All	All	All	All	All	All	All
United Kingdom	Some	All	All	All	All	All	All	All	All

This table presents strategy performance comparison across different data series. “All” means that all TTR strategy specifications outperform a buy-and-hold. This includes the moving average, time-series and mixed trading strategies. “Some” indicates that at least once the BH is not outperformed.

Table 12: Avoiding largest losses across countries

Country	Period	-0.5 %	-1.0 %	-1.5 %	-2.0 %	-2.5 %	-3.0 %	-3.5 %	-4.0 %
Australia	All	37	47	52	60	73	80	86	85
	Recessions	46	55	62	69	85	84	86	81
Austria	All	42	52	59	73	78	82	88	88
	Recessions	49	60	70	83	89	90	93	94
Belgium	All	40	53	64	71	76	86	90	94
	Recessions	64	74	82	86	91	97	95	97
Brazil	All	36	39	42	50	56	64	72	79
	Recessions	57	62	66	74	81	88	89	90
Chile	All	47	58	64	70	80	79	74	73
	Recessions	66	75	79	81	95	93	91	100
China	All	50	51	50	47	44	43	40	39
	Recessions	54	55	56	54	52	53	50	49
Colombia	All	45	52	58	62	65	74	89	100
	Recessions	56	68	73	78	86	84	93	100
Denmark	All	34	42	51	56	62	72	62	68
	Recessions	46	58	66	70	73	79	74	76
Egypt	All	38	43	46	50	50	56	63	62
	Recessions	84	87	85	86	89	90	96	100
Finland	All	40	47	54	59	65	70	73	76
	Recessions	56	65	71	75	80	84	85	87
France	All	44	54	63	68	77	86	89	94
	Recessions	69	75	80	84	88	90	95	96
Germany	All	44	52	61	64	72	81	92	97
	Recessions	56	64	72	78	86	91	98	100
Greece	All	57	63	68	71	75	78	80	85
	Recessions	71	78	84	86	89	91	91	97
Hong Kong	All	40	46	52	57	60	64	65	66
	Recessions	76	81	82	83	86	88	87	83
Hungary	All	40	44	50	54	59	65	69	70
	Recessions	53	61	70	80	81	85	90	90
India	All	43	45	48	51	51	50	53	53
	Recessions	59	62	66	67	71	68	67	64
Indonesia	All	41	46	49	55	57	61	63	64
	Recessions	59	66	69	76	77	77	85	87
Ireland	All	39	47	55	61	69	76	78	82
	Recessions	50	58	67	73	79	85	86	89
Italy	All	50	58	65	70	77	84	87	92
	Recessions	73	80	84	86	90	93	92	92
Japan	All	53	59	65	67	70	69	76	77
	Recessions	65	70	76	81	86	83	88	87
Malaysia	All	48	58	64	68	66	65	62	55
	Recessions	78	79	79	80	73	74	69	64
Mexico	All	38	42	48	56	66	69	77	82
	Recessions	63	69	77	84	91	93	93	91
Netherlands	All	41	50	60	67	73	86	90	97
	Recessions	61	71	79	85	88	95	96	100
New Zealand	All	34	40	48	48	53	52	56	58
	Recessions	46	55	63	67	60	42	50	50
Norway	All	38	45	53	60	67	76	78	78
	Recessions	55	63	69	73	80	92	90	93
Philippines	All	46	50	55	57	65	68	68	70
	Recessions	87	91	93	96	97	96	100	100
Poland	All	41	47	54	55	60	66	68	65
	Recessions	55	62	69	71	78	85	90	94
Portugal	All	51	59	69	76	80	82	87	89
	Recessions	69	76	83	88	90	92	96	100
Singapore	All	47	56	62	67	70	74	76	83
	Recessions	93	91	92	93	96	100	100	100
South Africa	All	28	34	42	52	61	68	76	86
	Recessions	43	53	66	75	86	90	95	94
South Korea	All	51	55	58	61	62	65	68	70
	Recessions	67	74	80	85	87	91	92	93
Spain	All	47	57	64	73	80	85	91	90
	Recessions	62	70	77	84	87	87	93	93
Sweden	All	39	47	55	63	68	71	71	74
	Recessions	64	71	77	82	86	86	86	86
Switzerland	All	43	54	64	72	76	86	90	90
	Recessions	63	74	83	90	90	92	95	95
Taiwan	All	48	54	58	62	63	63	67	73
	Recessions	80	81	81	86	87	88	94	96
Thailand	All	47	51	54	56	62	64	65	65
	Recessions	75	75	77	76	77	83	81	77

Turkey	All	37	40	46	50	53	55	51	53
	Recessions	56	61	66	74	76	72	71	78
United Kingdom	All	41	52	62	71	80	86	90	95
	Recessions	52	63	74	81	86	92	96	100

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 size of the shock. The second column indicates whether the shocks are collected over the whole sample period or during recession periods of the country indicated in the first column.

Table 13: International indices and financial development

	MA(1,150)	MA(5,150)	AR(100)	AR(200)	Mix(1,150)	Mix(5,150)
VaR 2.5%	0.15	0.16	0.11	0.12	0.15	0.15
	[3.03]***	[3.12]***	[3.27]***	[3.39]***	[3.12]***	[3.20]***
Efficiency	-0.13	-0.12	-0.13	-0.16	-0.13	-0.12
	[-2.26]**	[-2.03]**	[-3.14]***	[-3.82]***	[-2.32]**	[-2.22]**
Depth	0	-0.01	0	0	0	0
	[-0.16]	[-0.23]	[0.14]	[0.01]	[0.06]	[-0.01]
Constant	0.12	0.07	0.12	0.12	0.1	0.07
	[0.90]	[0.52]	[1.36]	[1.24]	[0.79]	[0.57]
R-squared	0.24	0.24	0.31	0.36	0.25	0.25

This table presents the coefficient estimates of regressing the measured risk reduction for each country on financial (stock) market development indicators and the initial level of risk. Var 2.5% is the initial level of risk for the country index. Efficiency is proxied by a country's stock market turnover ratio and Depth is proxied by a country's stock market capitalization to GDP ratio. The financial development indicators are measured as the average over the stock's sample period. The first row indicates for which TTR risk reduction is measured. T-statistics for the regression coefficients are given in parentheses, where the stars indicate 10%, 5%, or 1% significance level. The data is from the World Bank database.

Table 14: Reality check bootstrap

	Strategy	Performance	P-Value
Sharpe ratio	EGarch(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	1.33	0
VaR 1.0%	MA(1,50) d=0	1.97	0
VaR0.05%	MA(1,50) d=0.1	2.65	0
ES 2.5%	MA(1,50) d=0.1	2.32	0
ES 1.0%	MA(1,50) d=0.1	3.43	0
ES 0.5%	MA(1,50) d=0.1	4.61	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.

Table 15: Risk measures of moving 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%
E[R]	0.07	0.06	0.06	0.06	0.06	0.06	0.06	0.07	0.07	0.07	0.07
	-	(0.87)	(0.87)	(0.74)	(0.75)	(0.71)	(0.7)	(0.53)	(0.56)	(0.54)	(0.54)
SR	0.26	0.30	0.31	0.34	0.34	0.35	0.35	0.39	0.40	0.39	0.38
	-	(0.27)	(0.29)	(0.13)	(0.15)	(0.11)	(0.11)	(0.04)	(0.05)	(0.04)	(0.03)
MDD	89.19	49.35	49.39	49.94	51.08	42.04	42.93	46.61	48.88	50.23	48.29
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Worst year	-54.13	-23.48	-22.94	-25.37	-25.60	-19.92	-19.44	-24.08	-25.07	-31.54	-31.54
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 2.5%	2.17	1.42	1.43	1.48	1.48	1.48	1.48	1.48	1.48	1.48	1.48
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 1.0%	3.10	2.06	2.06	2.09	2.09	2.12	2.13	2.11	2.11	2.12	2.12
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 0.05%	4.01	2.54	2.51	2.59	2.59	2.61	2.61	2.62	2.62	2.62	2.62
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 2.5%	3.32	2.19	2.19	2.24	2.24	2.26	2.27	2.26	2.25	2.26	2.26
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 1.0%	4.49	2.94	2.94	3.00	3.00	3.03	3.05	3.03	3.03	3.04	3.04
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 0.5%	5.50	3.61	3.61	3.70	3.70	3.73	3.76	3.73	3.73	3.75	3.75
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)

This table reports statistics on performance and risk for moving average trading strategies, including 0.15% 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, 2021.

Table 16: Risk measures 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%
E[R]	0.07	-0.01	0.05	0.00	0.06	0.00	0.06	0.02	0.06	0.00	0.05
	-	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)
SR	0.26	-0.27	0.24	-0.16	0.29	-0.15	0.29	-0.03	0.28	-0.19	0.19
	-	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)
MDD	89.19	95.42	72.91	87.72	69.55	91.02	70.33	88.66	77.47	94.94	72.63
	-	(0.09)	(1)	(0.06)	(0.96)	(0.15)	(0.98)	(0.18)	(0.89)	(0.19)	(0.99)
Worst year	-54.13	-38.78	-38.22	-33.94	-32.38	-28.87	-34.33	-35.09	-38.08	-49.72	-33.23
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0.25)	(0.34)
VaR 2.5%	2.17	1.61	1.57	1.60	1.56	1.63	1.61	1.74	1.78	1.59	1.60
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 1.0%	3.10	2.27	2.25	2.25	2.25	2.33	2.33	2.51	2.57	2.33	2.33
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 0.05%	4.01	2.89	2.84	2.88	2.94	3.04	3.03	3.25	3.27	3.09	3.07
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 2.5%	3.32	2.46	2.42	2.45	2.46	2.54	2.52	2.75	2.80	2.54	2.56
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 1.0%	4.49	3.33	3.29	3.31	3.38	3.45	3.45	3.77	3.85	3.53	3.57
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 0.5%	5.50	4.14	4.09	4.12	4.23	4.30	4.30	4.71	4.81	4.44	4.51
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)

This table reports statistics on performance and risk for time-series trading strategies, including 0.15% 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, 2021.

Table 17: Risk measures 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%
E[R]	0.07	0.06	0.06	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
	-	(0.7)	(0.81)	(0.51)	(0.76)	(0.52)	(0.74)	(0.33)	(0.26)	(0.38)	(0.27)
SR	0.26	0.36	0.39	0.39	0.46	0.39	0.46	0.44	0.41	0.43	0.40
	-	(0.09)	(0.17)	(0.04)	(0.18)	(0.02)	(0.14)	(0)	(0)	(0.01)	(0)
MDD	89.19	56.08	47.06	46.86	34.64	37.60	34.53	37.22	53.79	43.18	54.66
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Worst year	-54.13	-27.61	-26.80	-30.35	-22.08	-21.27	-22.08	-23.93	-24.74	-23.23	-24.60
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 2.5%	2.17	1.42	1.47	1.49	1.47	1.49	1.48	1.48	1.50	1.49	1.50
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 1.0%	3.10	2.05	2.08	2.13	2.12	2.13	2.13	2.12	2.16	2.14	2.16
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
VaR 0.05%	4.01	2.50	2.57	2.64	2.64	2.63	2.64	2.62	2.73	2.63	2.73
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 2.5%	3.32	2.19	2.23	2.27	2.27	2.27	2.28	2.26	2.34	2.27	2.34
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 1.0%	4.49	2.95	2.99	3.05	3.06	3.05	3.07	3.03	3.19	3.05	3.19
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ES 0.5%	5.50	3.64	3.70	3.76	3.77	3.76	3.79	3.73	3.99	3.76	3.99
	-	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)

This table reports statistics on performance and risk for "mixed" trading strategies, including 0.15% 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, 2021.