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The predictive ability of technical trading rules: an empirical analysis of developed and emerging equity markets

Kevin Rink[1]

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Abstract
We investigate the predictability of leading equity indices of 23 developed and 18 emerging markets with a set of 6406 technical trading rules over up to 66 years. Using a state-of-the-art test for superior predictive ability to control for data snooping bias, we find in-sample evidence for technical heuristics with significant outperformance over a simple buy-and-hold strategy in the majority of markets. The proportion of heuristics with superior performance is much higher among emerging market indices, and the predictability diminishes drastically over time in all markets. In particular, markets turn unpredictable in the last years of our sample. Moreover, the results are very sensitive to the introduction of moderate transaction costs. An out-of-sample analysis shows that the performance of technical rules is not persistent in the sense that recently best-performing rules perform significantly worse than simple buy-and-hold strategies in the future. Overall, our results cast serious doubt on whether investors could have earned any excess profits using the broad range of considered technical trading rules.

Keywords Technical analysis · Predictive ability · Multiple hypothesis testing · Data snooping bias · Market efficiency · Transaction costs

JEL Classification C12 · C15 · G11 · G14 · G15

✉ Kevin Rink
krink@wiwi.uni-frankfurt.de

[1] Faculty of Economics and Business, Goethe University Frankfurt, Frankfurt, Germany

1 Introduction

Whether technical analysis is capable of generating consistent profits is a matter of intense debate, both in research and in practice. According to several academic studies, technical trading rules,[1] which generate trading signals solely based on past price and volume information, are popular among professional and retail investors.[2] However, proponents of the efficient market hypothesis (Fama 1965, 1970) argue that technical analysis is meaningless, such as Malkiel (1999) who states that "technical analysts build their strategies on dreams of castles in the air" (p. 138) and that these investors follow an "abnormally dedicated cult" (p. 119).

The empirical literature mainly disagrees on whether technical analysis adds value for investors.[3] Most of these studies, however, focus exclusively on the leading US stock market indices and investigate narrow sets of technical trading heuristics. In addition to that, the research on technical trading rules generally faces the challenge of an accurate statistical analysis, which is necessary to produce reliable results. Data snooping bias is a major concern when assessing multiple models at the same time, which is often the case in the research of technical trading rules.[4] Since the risk of data snooping bias is immense when analyzing large sets of trading rules simultaneously, a statistical procedure to account for data snooping is inevitable. However, adequately dealing with data snooping is technically challenging, such

[1] Throughout this paper, we use the terms "technical trading rules," "technical trading heuristics," or "technical trading strategies" interchangeably.

[2] For example, the survey studies by Hoffmann and Shefrin (2014) and Lease et al. (1974) suggest that about one-fourth to one-third of retail investors regularly use technical analysis to come up with trading decisions. Menkhoff (2010) shows that fund managers heavily rely on technical analysis to predict prices with a forecast horizon of less than two months. Survey responses analyzed by Cheung and Chinn (2001), Gehrig and Menkhoff (2003, 2004), and Menkhoff (1997) highlight the importance of technical trading for foreign exchange traders.

[3] Research results in favor of the use of simple technical trading heuristics in Western equity markets are provided by Alexander (1961, 1964), Benington and Jensen (1970), Bessembinder and Chan (1995), Brock et al. (1992), Hsu and Kuan (2005), Levy (1967a, 1967b, 1968), Neely et al. (2010), Neftci (1991), and Sullivan et al. (1999), among others. The empirical findings of Allen and Karjalainen (1999), Bajgrowicz and Scaillet (2012), Blume and Fama (1966), Day and Wang (2002), and Neely (2003) present empirical evidence against the profitability of technical trading rules. In addition, Hsu et al. (2016), Neely et al. (1997), Neely and Weller (2011), and Sweeney (1986) investigate applications of technical analysis in foreign exchange markets and find mixed results. Comprehensive reviews of the technical analysis literature are provided by Farias Nazário et al. (2017) and Irwin and Park (2007). Adekoya et al. (2019) review the literature on stock market predictability based on machine learning techniques, most often combined with technical analysis. A new strand of literature examines whether technical analysis is beneficial in cryptocurrency markets. Detzel et al. (2020) show theoretically that moving averages can add value for trading assets with hard-to-value fundamentals such as Bitcoin. Empirical support for technical trading in cryptocurrency markets is presented by Ahmed et al. (2019), Bazán-Palomino and Svogun (2022), Cohen (2021), and Hudson and Urquhart (2021). Hackethal et al. (2022) document that individual investors trading structured retail products for cryptocurrencies are also more likely to use moving average heuristics.

[4] Terms such as "*p*-hacking" or "data dredging" may be more common and are often used as synonyms for "data snooping" (see, for example, Harvey (2017) for a recent discussion of the problem of *p*-hacking in scientific research). The latter term is commonly used in the literature on technical analysis as well as on multiple hypothesis tests suitable for processing large sets of technical trading rules (e.g., Hansen 2005; Romano and Wolf 2005; Sullivan et al. 1999; White 2000). Therefore, we stick to this terminology in this paper as well.

that statistical tests that address this problem were not developed until after White (2000) introduced a "Reality Check" for data snooping. Irwin and Park (2007) argue that the technical rigor of previous studies is generally low due to outdated statistical procedures and that many of these positive contributions to the literature may be significantly flawed due to problems with data snooping.

This paper revisits the mixed results found by the previous literature, whose contributions are mainly limited in at least one of three dimensions: (i) the scope of investigated market data, (ii) the range of considered technical trading rules, and (iii) the adequacy of statistical tests to address concerns of data snooping bias. Our goal is to provide a comprehensive study that does not fall short on any of these points. We investigate the predictability of 23 developed and 18 emerging market indices with a set of 6406 common technical trading rules.[5] The sample includes daily close prices spanning up to 66 years.[6] We employ the "Stepwise Superior Predictive Ability Test" proposed by Hsu et al. (2010), which is a state-of-the-art multiple hypothesis test designed to assess the statistical significance of the performance of large sets of trading rules while controlling for data snooping bias. The test combines features of related multiple hypothesis tests of Hansen (2005) and Romano and Wolf (2005), and is able to identify as many predictive technical trading rules as possible in a stepwise procedure.[7]

We apply the Stepwise Superior Predictive Ability Test to all stock indices in our sample and find statistically significant outperformance of technical trading rules over simple buy-and-hold strategies in 13 of the 23 developed countries and in 14 of the 18 emerging markets based on a Sharpe ratio (Sharpe 1966, 1994) performance measure.[8] Particularly for developed market indices, the number of rules that outperform the respective index is generally low. We then divide the sample periods into subsamples of 7 years in length to examine the evolution of predictive ability over time. We find a significant time trend in the predictive power of technical rules, which is highest during the first subperiods and declines sharply thereafter. Almost no developed market is predictable with the considered technical trading rules during the last two

[5] It is important to note that our study focuses exclusively on the application of time series strategies at the index level and does not consider cross-sectional technical trading approaches such as momentum (Jegadeesh and Titman 1993; Rouwenhorst 1998) or contrarian strategies (Lo and MacKinlay 1990a). However, we include a wide range of moving average trading rules that can be considered a time series equivalent of cross-sectional momentum trading (see Marshall et al. 2017; Moskowitz et al. 2012). The previous literature has extensively covered cross-sectional momentum, with comprehensive reviews on the topic provided by, for example, Subrahmanyam (2018) and Wiest (2023).

[6] The covered sample periods depend on data availability and first stock exchange notation of national stock indices.

[7] A detailed discussion of data snooping and the test procedure to evaluate the performance of technical trading rules is provided in the next section.

[8] In this paper, we refer to technical trading rules whose performance is significantly better than that of a buy-and-hold benchmark strategy as "outperforming rules," "significantly performing rules," or "predictive rules." Similarly, we consider stock indices where the benchmark strategy is significantly outperformed by at least one technical trading rule as "predictable." Technical rules that have the highest performance in the entire sample of trading rules are referred to as "best-performing trading rules." However, these rules do not necessarily outperform the benchmark strategy with statistical significance.

subperiods starting in 2002. In contrast, we still find that half of the emerging markets are predictable, with at least one rule during the period between 2002 and 2008. However, in the last subperiod between 2009 and 2016, almost all emerging market indices are unpredictable. These in-sample results are consistent with the predictions of the adaptive market hypothesis of Lo (2004). In contrast to the efficient market hypothesis, the adaptive market hypothesis assumes that markets evolve over time and that efficiency gradually increases as market participants are subject to a steady learning process. The degree of efficiency and the speed of adjustment depends on the competition among traders and their ability to learn. Consequently, initially superior (proprietary) trading strategies may eventually turn unprofitable due to either changing market environments or excessive competition as more participants adopt these strategies. In line with that, for all markets in our sample, the predictability through technical trading rules vanishes over time, and markets that are assumed to be less competitive generally exhibit higher predictability through technical trading rules.

Next, we test for the sensitivity of technical trading to transaction costs. In contrast to the previous literature, we refrain from calculating simple break-even transaction costs for technical rules. This approach treats transaction costs as exogenous and, thereby, neglects the impact of these costs on the performance of trading rules relative to each other.[9] We circumvent this issue by running the Stepwise Superior Predictive Ability Test multiple times with steadily increasing single-trip transaction costs. The analysis reveals that the predictive power of many rules is quickly offset by the introduction of low transaction costs. Only 5 of the 23 developed markets and 4 of the 18 emerging markets exhibit significantly outperforming trading rules for single-trip transaction costs of at least 20 basis points. The high sensitivity of technical trading performance to transaction costs is in line with prior findings in the literature (e.g., Allen and Karjalainen 1999; Bajgrowicz and Scaillet 2012; Ready 2002).

A significant part of this paper is devoted to an out-of-sample analysis on the applicability of technical heuristics in a way that aims to mimics the trading behavior of a real trader. Most of the previous literature on technical analysis examines only the ex-post performance of technical heuristics and neglects whether these heuristics actually exhibit out-of-sample persistent performance in the future. We identify the best trading rules in 3 year subperiods that are eligible for trading in each subsequent 3 year period. While the in-sample performance in terms of Sharpe ratios of the best trading rules is highly economically and statistically significant, the corresponding out-of-sample performance relative to buying and holding the respective index is either insignificant or negative and significant.[10] We also construct three equally weighted portfolios based on the out-of-sample technical trading algorithm applied to all 41 markets, as well as all developed markets and all emerging markets, respectively. Assuming transaction costs of zero, we find that none of the

[9] In particular, the performance of technical rules that generate trading signals less frequently tends to be less sensitive to transaction costs. Thus, if transaction costs are high, heuristics with few trading signals may (all else equal) perform better than others that generate more frequent trading signals.

[10] In-sample performance is measured with the trading rule with the highest Sharpe ratio during a 3 year period. In contrast, out-of-sample performance is measured with the Sharpe ratio of the trading rule that had the highest Sharpe ratio during the previous 3 year period.

three portfolios generates a Sharpe ratio that is significantly different from the ones of the equally weighted buy-and-hold portfolios. For positive transaction costs, the technical trading portfolios significantly underperform the buy-and-hold portfolios most of the time. These findings suggest that the performance of best rules is not persistent and technical trading signals can be considered as noise.

We contribute to the empirical literature with a clear argument against the usefulness of technical trading rules in today's markets. We consider this contribution significant for several reasons. To the best of our knowledge, this paper is the first broad-based analysis using the powerful and rigorous Stepwise Superior Predictive Ability Test for an analysis of technical trading rules in a comparative analysis of equity markets.[11] In addition, we leverage the test procedure to determine the distribution of rules with superior performance at different transaction cost levels. Unlike existing transaction cost analyses in the literature, we do not perform a pure break-even analysis, which may be biased since transaction costs are treated as exogenous. Another contribution is the out-of-sample test for technical trading performance. A similar persistence analysis has only been conducted by Bajgrowicz and Scaillet (2012), who apply it to a single time series of daily index data. To the best of our knowledge, our study provides the most comprehensive analysis of a large set of technical trading rules in terms of the number of investigated stock markets, the power of the applied testing procedure, and the rigor of the transaction cost and out-of-sample analysis. Given the general disagreement in the academic literature on the predictive ability of technical trading rules, our work aims to shed light on this ongoing debate.

The remainder of this paper is organized as follows. Section 2 discusses data snooping bias and multiple hypothesis tests in research on technical trading rules. Section 3 introduces the technical trading rules used in the empirical analysis of this paper. Section 4 deals with the performance measurement. Section 5 describes the data. Sections 6 and 7 present the in-sample and out-of-sample results, respectively. Section 8 concludes.

2 Data snooping bias and research on technical analysis

In the following, we provide a discussion of data snooping and appropriate testing procedures to cope with it in the context of technical analysis. While this section is mainly nontechnical, Appendix 1 introduces the basic steps required to implement the Stepwise Superior Predictive Ability Test by Hsu et al. (2010) used in the empirical part of this paper.

[11] Jiang et al. (2019) use the Stepwise Superior Predictive Ability Test to study technical trading in the Chinese stock market. They report evidence for superior in-sample performance of some rules compared with a buy-and-hold strategy. Furthermore, Chen et al. (2015) analyze the profitability of candlestick trading strategies applied to stocks listed in the Dow Jones Industrial Average (DJIA) and report positive results. Prior studies, such as the seminal paper by Sullivan et al. (1999) examines a similar set of rules in the US stock market. However, the paper relies on the Reality Check of White (2000), which can only evaluate the statistical significance of the best trading rule from a potentially large set of rules.

Data snooping becomes a problem if data are used more than once for statistical inference or to assess the applicability of multiple models (White 2000). This occurs frequently in empirical research as prior empirical findings likely motivate researchers to reexamine already investigated data (Lo and MacKinlay 1990b). Thus, datasets that happen to yield "desired" results are likely studied more intensively, while other datasets may be studied less frequently and the corresponding results are rarely published. With respect to that, Merton (1987) stresses the potential for biased results due to an overuse of certain data. He argues that standard statistical tests are inappropriate for these applications as they do not account for potential biases caused by data snooping. In addition, data snooping bias is a concern when multiple hypotheses are evaluated based on one dataset. One may (unintentionally) over adjust and fine tune the parametrization of technical heuristics based on past information, and succumb to the impression of superior performance. Thus, technical analysis research is highly susceptible to data snooping bias due to the large number of potentially testable trading rules. Bajgrowicz and Scaillet (2012) exemplify the danger of data snooping with the following exaggerated example: "[I]magine you put enough monkeys on type writers and that one of the monkeys writes 'The Iliad' in ancient Greek. Because of the sheer size of the sample, you are likely to find a lucky monkey once in a while. Would you bet any money that he is going to write 'The Odyssey' next?" (p. 474). The essence of data snooping bias is, therefore, that ample search for successful trading rules (or, more generally, for some models) in past data may likely yield superior but spurious results.

Classical hypothesis testing procedures disregard the impact of search on statistical significance in problems involving a high number of models to be evaluated. Following the argument of Hsu et al. (2016), if one aims to test for statistical significance of the maximum element from the vector $\theta = \left(\theta_1, \theta_2, \ldots, \theta_m\right)$ (e.g., the highest performance measure from a set of m trading rules), a traditional test setup may simply formulate a null hypothesis based on the maximum element of θ, $\theta^{\max} = \max\left\{\theta_1, \theta_2, \ldots, \theta_m\right\}$. However, according to White (2000), if an extensive specification search is required to identify the best-performing forecasting model, there is a high risk that the performance of this model is spurious. Even if one is only interested in the significance of the best model, the search process involved in identifying such a model implicitly turns the setup into a multiple hypothesis problem. That is because weaker models are also evaluated along the search process. As a result, neglecting the specification search and, thus, disregarding worse models in the test procedure of the best model increases the probability of committing a type I error of incorrectly rejecting the null hypothesis. Hence, for large m, one likely overstates the statistical significance of the highest performance in θ and understates the actual probability of a type I error if the test procedure does not account for data snooping. This concern is particularly pronounced when testing technical trading rules, as the free choice of parameter values typically leads to many different (albeit correlated) models.

An early and simple approach to account for multiple hypotheses in statistical tests is provided by the popular Bonferroni correction. If one targets an overall significance level (often referred to as familywise error rate) of α while testing m models simultaneously, the Bonferroni correction requires that each model is tested with

a significance level of α/m. This approach might be suitable for applications where m is small. However, the test becomes very conservative for large m.[12] Also, the Bonferroni correction disregards a potentially complex correlation structure of trading signals of "related" trading rules.[13] The higher the correlation, the more conservative a Bonferroni test is. In the extreme case of a perfect correlation between all considered trading rules, a multiple hypothesis test is equivalent to a single hypothesis test. An appropriate test for evaluating the performance of technical trading rules should take this correlation into account.

White (2000) is the first to propose a joint testing method that considers the dependence structure of individual time series. His Reality Check tests whether the best trading rule from a potentially large set of trading rules shows significant outperformance of a benchmark such as a buy-and-hold strategy. White (2000) encounters the problem that the distribution of $\theta^{\max}$ from the vector θ with correlated elements is highly complex or unknown (e.g., if the elements of θ are correlated normal random variables, the distribution of $\theta^{\max}$ is unknown). White (2000) shows that a null hypothesis of the form $\mathrm{H}_0 : \max_{k=1,\ldots,m} \theta_k \leq 0$ can be tested using the stationary bootstrap of Politis and Romano (1994). According to that, the original data are resampled in blocks of stochastic length to obtain pseudo time series that are used to compute an empirical bootstrap distribution for $\theta^{\max}$. The p-value for the best model is then calculated as the proportion of bootstrapped maximum performance measures that are larger than the actual sample maximum.

The Reality Check has two limitations from a statistical and a practical perspective. First, as Hansen (2005) notes, the Reality Check has low statistical power if many poorly performing trading rules are tested. This is because an increasing number of poor models disguises the good ones, resulting in lower test power.[14] Second, the Reality Check only tests for the significance of $\theta^{\max}$, such that there is no statistical evaluation of all strategies that are inferior to the best strategy. In practice, however, it may not be sufficient to just assess the statistical significance for the best trading rule, since one may be interested in all rules that exhibit real outperformance.

Both drawbacks of White's (2000) Reality Check are addressed in advanced versions of the test. Hansen (2005) proposes the "Superior Predictive Ability Test," an improved version of the Reality Check in which bootstrap samples are recentered when models perform particularly poorly, assigning lower weights to those models. Still, the Superior Predictive Ability Test also just tests the single best model, regardless of the total number of considered models. Both Romano and Wolf (2005) and Hsu et al. (2010) introduce stepwise versions of the Reality Check and the Superior

[12] For instance, testing the 6406 trading rules used in our empirical analysis at $\alpha = 0.1$ yields an individual significance level of less than 0.000016 for each trading rule.

[13] The large number of trading rules used in this studied mainly results from slight parameter variations, so that the generated trading signals typically cluster within short time periods for heuristics with similar parameterization (see Etheber 2014).

[14] This effect can be exemplified by the Bonferroni correction as noted by Hsu et al. (2016). If one raises the number of poor models, the familywise error rate declines and the hurdle to reject the null hypothesis for the performance of the best model increases. This makes it less likely that significant outperformance will be detected.

Predictive Ability Test, respectively. These tests extend the existing counterpart by an algorithm that allows to identify all models with statistically significant outperformance in a stepwise procedure that asymptotically controls for the probability of committing a type I error. If the full set of models contains models with superior performance, these are removed from the full set and the procedure is reestimated over the remaining subset. This stepwise procedure terminates as soon as the test no longer identifies a model that exhibits superior performance at the prespecified significance level. For our empirical study, we employ the Stepwise Superior Predictive Ability Test of Hsu et al. (2010), as it is the most progressive test procedure by combining the Superior Predictive Ability Test of Hansen (2005) with a stepwise algorithm.[15]

3 Technical trading rules

We use a sample of 6406 technical trading rules that are categorized in five major strategy classes. For some rules, we additionally use up to three trading filters. While we briefly introduce these five strategies and three trading filters here, Appendix 2 provides the technical definitions required to implement them for computer-based automated trading.

The relative strength index is a so-called oscillator, which was first introduced and studied by Levy (1967a, 1967b) and Wilder (1978). It defines a ratio of the sum of positive to the sum of all absolute price changes over a prespecified time period. The frequency and the magnitude of positive price changes raises the relative strength index. Analogously, negative price changes decrease the relative strength index. By definition, the index ranges from 0 to 100. Technical analysts interpret a high relative strength index (usually values of 70 and above are considered high) as an indication of a recently overbought stock that is expected to undergo a downward correction in the near future. A value of 30 or below is usually interpreted in the other direction.

Filter rules were studied by Alexander (1961, 1964) as well as Blume and Fama (1966). These rules assume that recent trends in stock prices are likely to continue in the future. Trading signals are generated once a stock shows a trend (i.e., positive or negative cumulative price changes of a certain magnitude) during a specific period of time. Adverse price movements indicate the reversal of trends.

Moving average rules attempt to identify price trends by smoothing the time series of past prices. Trading signals are triggered when two moving averages cross which is perceived as a reversal of a trend. Specifically, once the “slow” moving average (i.e., the smoother moving average due to an inclusion of more historical data) penetrates

[15] A recent strand of the literature introduces the false discovery rate methodology to evaluate the performance of portfolios formed with technical trading rules (cf., Bajgrowicz and Scaillet 2012). Introduced by Benjamini and Hochberg (1995) and first employed for finance applications by Barras et al. (2010), the technique reduces the number of false positives in multiple hypothesis testing by allowing a small fraction of false discoveries. The false discovery rate approach is a suitable alternative to the data snooping methods presented in this section.

the "fast" moving average from above, the crossover event is interpreted as a bullish signal. Likewise, a penetration from below is interpreted as a bearish signal.

Support and resistance rules rely on the assumption that the security price has not moved below or above a certain price level several times in the recent past (i.e., the price has formed a "support level" from above or a "resistance level" from below). Once a price breaks through the support level or falls below the resistance level, it is assumed to continue moving in the respective direction.

Channel breakout rules are based on the idea that a security price moves within the boundaries of a certain price range. More specifically, a channel is defined by two parallel lines between which the price moves back and forth over a specific period of time. A break through the upper (lower) boundary of the channel is interpreted as the beginning of a positive (negative) trend.

We supplement the trading rules with up to three common trading filters.[16] These filters are designed to improve trading results by filtering out "unfavorable" trading signals ex ante.[17] First, a band filter sets an additional return by which the price of an asset must move in the desired direction to open a trading position after a trading signal is generated. It is, therefore, designed to prevent the entry into a position if the price movement is not strong enough. Second, a time-delay filter simply delays a trade by a specified time interval after a signal is generated. Third, a fixed-length filter defines a fixed holding period after which a position is automatically liquidated. Any intermediate trading signals are ignored. This filter aims to close a position before trends flatten out and the security potentially generates negative returns.

The filter, moving average, support and resistance, and channel breakout rules as well as their parameterizations are adopted from the seminal paper of Sullivan et al. (1999). In contrast to their study, this paper does not use on-balance volume rules (that require daily volume data) because volume data are not available for several indices in our sample. We, furthermore, add the relative strength index rules used by Hsu et al. (2016) to our sample of rules. The parameters of the trading rules are presented in Table 1 and Table 2 lists the considered parameter combinations. Overall, we study a total of 6406 trading rules, including 600 relative strength index rules, 497 filter rules, 2049 moving average rules, 1220 support and resistance rules, and 2040 channel breakout rules.

4 Performance measurement

Similar to the prior literature (e.g., Bajgrowicz and Scaillet 2012; Hsu et al. 2010, 2016; Sullivan et al. 1999), we use a Sharpe ratio criterion in all applications of the Stepwise Superior Predictive Ability Test to evaluate the performance of technical trading rules (see Appendix 1 for the implementation of the test procedure based

[16] To avoid confusion, we note that filter rules are a standalone class of technical trading heuristics, while trading filters are used to refine any type of technical trading rule.

[17] See, for instance, Bajgrowicz and Scaillet (2012), Brock et al. (1992), Hsu et al. (2016), and Sullivan et al. (1999) for applications of trading filters in the empirical literature as well as, for instance, Pring (2014) for a discussion on the topic in the mainstream technical analysis literature.

on the Sharpe ratio criterion, which is introduced in this section). To formalize the underlying performance measurement, let there be a total of m trading heuristics to be tested and let r_t denote the one-period return of a certain risky asset and r_t^f denote the risk-free rate in period t, $t = 1, \ldots, N$. Furthermore, $\delta_{t-1,k}$ is a signal indicator for heuristic k, $k = 1, \ldots, m$, which indicates the exposure to the security in period t (i.e., $\delta_{t-1,k} = 1$ for a long, $\delta_{t-1,k} = 0$ for a neutral, and $\delta_{t-1,k} = -1$ for a short position).

Trading according to technical sell signals requires closing long positions and/or entering short positions, where the latter may be associated with several constraints such as lending fees, lacking assets to sell short, or governmental or institutional restrictions (see, e.g., Almazan et al. 2004; D'Avolio 2002; Nagel 2005). Short sale constraints are likely severe for certain markets and time periods in our sample. On the one hand, less-developed equity markets may not be endowed with the institutional framework for short selling (at reasonable costs). On the other hand, during earlier time periods, short selling was much more expensive than it became more recently (D'Avolio 2002; Duffie et al. 2002; Jones and Lamont 2002). Moreover, short selling costs are time varying and tend to increase substantially during periods with a high willingness of investors to short a stock.

We circumvent the problems associated with true short positions by using the "double-or-out" strategy proposed by Bessembinder and Chan (1995). According to that, whenever $\delta_{t-1,k} = 0$, an investor holds one unit of the asset and earns its return r_t. If $\delta_{t-1,k} = 1$, an investor is required to double his or her exposure by borrowing money at the risk-free rate to finance the additional unit of the asset that results in a payoff of $2r_t - r_t^f$. Finally, whenever $\delta_{t-1,k} = -1$, the asset is sold and the proceeds are invested in the risk-free security such that the payout is equal to r_t^f. In summary, the return of trading rule k in period t under a double-or-out strategy reads as

$$\pi_{t,k}(r_t, r_t^f, \delta_{t-1,k}) = \begin{cases} 2r_t - r_t^f, & \delta_{t-1,k} = 1, \\ r_t, & \delta_{t-1,k} = 0, \\ r_t^f, & \delta_{t-1,k} = -1, \end{cases} \tag{1}$$

and the associated Sharpe ratio is given by

$$S_k = \frac{\bar{\pi}_k - \bar{r}^f}{\hat{\sigma}_k}, \tag{2}$$

where $\bar{\pi}_k - \bar{r}^f$ is the sample average of excess returns and $\hat{\sigma}_k$ is the corresponding standard deviation.

We evaluate the performance of technical trading rules against a benchmark. A natural choice for a benchmark model is the null model of staying out of the market (e.g., Brock et al. 1992). However, since active traders usually aim to evaluate their trading performance against a benchmark that is related to the risk–return profile of the traded asset, we chose a simple buy-and-hold strategy as benchmark model. Therefore, we set $\pi_{t,0} = r_t \delta_{t,0}$, where $\delta_{t,0} = 1$ for all t such that $\pi_{t,0} = r_t$.

Following Sullivan et al. (1999), our final performance measure is the difference between the Sharpe ratios generated by trading rule k and the benchmark,

Table 1 Parameters of technical trading rules

Trading rule parameters	Parameter values
Relative strength indices, *RSI*(n, v, d,f_l)	
Moving average in days, n	5, 10, 15, 20, 25, 50, 100, 150, 200, 250
Deviation from $RSI = 50$, v	10, 15, 20, 25
Minimum number of days in overbought/oversold levels, d	1, 2, 5
Fixed holding period in days, f_l	1, 5, 10, 25
Filter rules, *FR*(x, e, y, f_l)	
Filter parameter, x	0.005, 0.01, 0.015, 0.02, 0.025, 0.03, 0.035, 0.04, 0.045, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 0.12, 0.14, 0.16, 0.18, 0.2, 0.25, 0.3, 0.4, 0.5
Alternative definition of extrema in days, e	1, 2, 3, 4, 5, 10, 15, 20
Price deviation required to unwind a position, y	0.005, 0.01, 0.015, 0.02, 0.025, 0.03, 0.04, 0.05, 0.075, 0.1, 0.15, 0.2
Fixed holding period in days, f_l	5, 10, 25, 50
Moving averages, *MA*(n_s, n_f,f_b,f_d,f_l), $n_s > n_f$	
Slow-moving average in days, n_s	2, 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 200, 250
Fast-moving average in days, n_f	1, 2, 5, 10, 15, 20, 25, 30, 40, 50, 75, 100, 125, 150, 200
Multiplicative band filter, f_b	0.001, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, 0.05
Time-delay filter in days, f_d	2, 3, 4, 5
Fixed holding period in days, f_l	5, 10, 25, 50
Supports and resistances, n, e,f_b,f_d,f_l	
Support and resistance window in days, n	5, 10, 15, 20, 25, 50, 100, 150, 200, 250
Alternative definition of extrema in days, e	2, 3, 4, 5, 10, 20, 25, 50, 100, 200
Multiplicative band filter, f_b	0.001, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, 0.05
Time-delay filter in days, f_d	2, 3, 4, 5
Fixed holding period in days, f_l	5, 10, 25, 50
Channel breakouts, $CB(n,x,f_b,f_l)$	
Channel window in days, n	5, 10, 15, 20, 25, 50, 100, 150, 200, 250
Multiplicative range of channel, x	0.005, 0.01, 0.02, 0.03, 0.05, 0.075, 0.1, 0.15
Multiplicative band filter, f_b	0.001, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, 0.05
Fixed holding period in days, f_l	5, 10, 25, 50

This table reports the parameters for the trading rules used in the empirical analysis. Parameter values for relative strength index rules are adopted from Hsu et al. (2016). Parameters for filter rules, moving average rules, support and resistance rules, as well as channel breakout rules are adopted from Sullivan et al. (1999)

$$\theta_k = \frac{\bar{\pi}_k - \bar{r}^f}{\hat{\sigma}_k} - \frac{\bar{r} - \bar{r}^f}{\hat{\sigma}_0}, \tag{3}$$

where $\hat{\sigma}_0$ is the sample standard deviation of the return series of the benchmark.

Table 2 Parameter combinations of technical trading rules

Trading strategy classes	Parameter combinations
Relative strength indices	$\#n \cdot \#v \cdot \#d + \#n \cdot \#v \cdot \#d \cdot \#f_l = 10 \cdot 4 \cdot 3 + 10 \cdot 4 \cdot 3 \cdot 4 = 600$
Filter rules	$\#x + \#x \cdot \#e + \#x \cdot \#f_l + \sum_{i=1}^{\#x} \sum_{j=1}^{\#y} \mathbb{1}\{x(i) > y(j)\} = 24 + 24 \cdot 8 + 24 \cdot 4 + 185 = 497$
Moving averages	$(1 + \#f_b + \#f_d + \#f_l) \cdot \sum_{i=1}^{\#n_s} \sum_{j=1}^{\#n_f} \mathbb{1}\{n_s(i) > n_f(j)\} + 9 = (1 + 8 + 4 + 4) \cdot 120 + 9 = 2{,}049$
Supports and resistances	$(1 + \#f_l) \cdot (\#n + \#e) + \#f_b \cdot (1 + \#f_l) \cdot (\#n + \#e) + \#f_d \cdot \#f_l \cdot (\#n + \#e) = (1 + 4) \cdot (10 + 10) + 8 \cdot (1 + 4) \cdot (10 + 10) + 4 \cdot 4 \cdot (10 + 10) = 1{,}220$
Channel breakouts	$(\#n \cdot \#x \cdot \#f_l) + \#n \cdot \#f_l \cdot \sum_{i=1}^{\#x} \sum_{j=1}^{\#f_b} \mathbb{1}\{x(i) > f_b(j)\} = (10 \cdot 8 \cdot 4) + 10 \cdot 4 \cdot 43 = 2{,}040$

This table reports the parameter combinations for the trading rules used in the empirical analysis. Heuristics and parameters are defined in Table 1. $\#a$ denotes the number of considered parameter values of a parameter a, and $a(i)$ denotes the i-th parameter value of a, where parameter values are sorted in ascending order. $\mathbb{1}\{\cdot\}$ is the indicator function. Since we adopt all trading rules and parameters used by Sullivan et al. (1999) (except for on-balance volume rules), the set of moving average rules covers nine rules which are additionally added (these are all rules with a 1% band filter and a 10 day fixed-length filter applied to all moving average combinations of a 1, 2, and 5 day fast-moving average and a 50, 150, and 200 day slow-moving average). The nine rules are added as Sullivan et al.'s (1999) set of rules is designed to include all rules used by Brock et al. (1992)

Since we do not have interest rate data for most of the investigated markets, we set $r_t^f = 0$ for all t. Even though this simplification may bias our results, we assume that the impact on the overall outcomes is negligible. First, if a trading rule exhibits more days with long than short exposure, the trading returns may be biased upwards as we disregard longer periods when the investor has to pay r_t^f for borrowing funds to invest in a second unit of the asset. In turn, the performance could be biased downwards in the opposite case. Second, if costs of borrowing vary systematically between periods with long and short exposure, the performance measure may be biased as well. Third, expression (3) shows that the impact of $\bar{r}^f$ is approximately offset if standard deviations are similar. However, the performance of trading rule k tends to be overestimated if $\hat{\sigma}_0 > \hat{\sigma}_k$ when neglecting $\bar{r}^f$. For those reasons, we examine whether the simplification could have a significant impact on the performance measure. We find that the vast majority of investigated trading rules are relatively balanced in terms of the time invested in short and long positions. Moreover, the returns from technical trading tend to be more volatile than those of the respective benchmarks (which is mainly due to the characteristics of the double-or-out strategy), suggesting that setting $r_t^f = 0$ may keep our results rather on the conservative side. Based on these findings, we expect that the likelihood of a significant upward bias should be low.

5 Data

The empirical study is based on the daily close prices of the leading stock market indices of 23 developed countries and 18 emerging markets. An overview of these markets and respective sample periods is provided in Table 3. The longest available time series is for the US S&P 500, which covers the period between January 1950 and May 2016, while the shortest is for the Colombian IGBC, which covers the period between July 2001 and May 2016. The index data are retrieved from Datastream and cover the maximum available sample periods ending in May 2016. Markets for which less than 14 years of data are available are not included to ensure appropriately long time series and to have at least two subsamples of 7 years each in the subperiod analysis. The classification of countries as either "developed" or "emerging" is based on the categorization of the International Monetary Fund (IMF 2016), which applied at the end of the sample period. The 23 developed countries are considered as "advanced economies" by the IMF. Likewise, the 18 emerging markets are categorized as either emerging or developing markets.[18] Obviously, some of the markets undergo significant economic development during the sample period in the sense that some countries were not considered developed at the beginning of the sample period, but are considered so at the

[18] The IMF does not differentiate between emerging and developing markets in a stricter sense. However, the countries in our list are generally considered as emerging markets by most analyst firms. For instance, Financial Times Stock Exchange (FTSE) Group (2016) lists all countries in our sample except for Argentina (which they have on their watch list as a candidate) as either "advanced emerging," "secondary emerging," or "frontier" countries in their Annual Country Classification Review from September 2016. For simplicity, we refer to all these countries as emerging markets throughout this paper.

end.[19] Clearly, a static classification of markets for longer time periods is not perfectly possible.

Given that many emerging economies in the sample experienced high levels of inflation in the past, we adjust stock market returns for inflation rates.[20] The annual inflation rates are obtained from World Bank Open Data. We compute inflation-adjusted daily returns as $r_t^{adj} = r_t^{unadj} - \log(1 + i_y)/252$, where r_t^{unadj} is the unadjusted daily index return on day t, and i_y is the corresponding discrete inflation rate in year y.

Table 4 presents basic descriptive statistics for the 41 stock market indices as well as annual inflation rates of the corresponding countries. Not surprisingly, emerging market indices in panel B tend to have higher average annualized returns and are more volatile than most developed market indices in panel A. Similarly, with a few exceptions such as Croatia, these countries have much higher inflation rates on average.

The use of index data is widespread in studies of technical trading rules, which is mainly due to the availability of long time series. A major drawback of such analyses is the limitation that stock indices cannot be traded directly. Investments that are closely related to the risk and return profile of stock indices are usually only possible through certain derivative instruments or exchange-traded funds. An obvious alternative to conducting our analysis would be to use actual market data for the constituent stocks of the considered indices, which is, however, not available for many markets in our sample. In the absence of reasonable alternatives, we therefore also rely on index data, but note that a broad analysis of actual stock data could enrich the technical analysis literature.

The analysis of index data raises additional issues that may lead to an upward bias of results. As shown by Scholes and Williams (1977), nonsynchronous trading of index constituents can lead to measurement error due to spurious serial dependence of index returns. As Ready (2002) notes, especially on days with technical trading signals, there may be systematic differences between the close price and the opening price of a stock index on the next trading day. First, imbalances in buy/sell orders caused by excess buy/sell interest at the close could reappear at the opening of the following trading day and lead to a systematic price movement. Typically, technical signals tend to exploit positive serial dependence since buy (sell) signals are often observed on days with large positive (negative) price movements (Bessembinder and Chan 1995). Moreover, if at least some close prices of the stocks included in the index are stale, partial adjustments on subsequent trading days may result in price changes biased in the same direction as those on previous days. The concern of stale prices is relatively low for very liquid stocks, but it tends to be higher if stocks trade at low volume (Campbell et al. 1993). Hence, biases induced by nonsynchronous

[19] For example, Hong Kong and Singapore are classified as developing countries by the United Nations in its 1974 World Economic Survey (United Nations 1975).

[20] Unless otherwise noted, the index returns in this study are always adjusted for inflation. For the sake of simplicity, we will not highlight this at every point.

Table 3 Stock indices and sample periods

ISO	Country	Stock market index	Sample period
Panel A: Developed countries			
AUS	Australia	All ordinaries	03/08/1984–31/05/2016
AUT	Austria	ATX	07/01/1986–31/05/2016
BEL	Belgium	Bel 20	02/01/1990–31/05/2016
CAD	Canada	S&P/TSX Composite Index	01/01/1969–31/05/2016
CHE	Switzerland	SMI	30/06/1988–31/05/2016
DEU	Germany	DAX	31/12/1964–31/05/2016
DNK	Denmark	OMX Copenhagen 20	04/12/1989–31/05/2016
ESP	Spain	IBEX 35	05/01/1987–31/05/2016
FIN	Finland	OMX Helsinki 25	02/01/1987–31/05/2015
FRA	France	CAC 40	09/07/1987–31/05/2016
GBR	UK	FTSE 250 Index	31/12/1985–31/05/2016
GRC	Greece	Athex Composite Index	01/03/1994–31/05/2016
HKG	Hong Kong	Hang Seng Index	21/11/1969–31/05/2016
ISR	Israel	TA-100 Index	23/04/1987–31/05/2016
ITA	Italy	FTSE MIB	01/01/1998–31/05/2016
JPN	Japan	Nikkei 225	03/04/1950–31/05/2016
KOR	South Korea	KOSPI	01/01/1975–31/05/2016
NLD	the Netherlands	AEX-Index	03/01/1983–31/05/2016
NOR	Norway	OBX Index	02/01/1987–31/05/2016
PRT	Portugal	PSI 20	01/01/1993–31/05/2016
SGP	Singapore	Straits Times Index	31/08/1999–31/05/2016
SWE	Sweden	OMX Stockholm 30	02/01/1986–21/04/2016
USA	USA	S&P 500 Index	03/01/1950–31/05/2016
Panel B: Emerging markets			
ARG	Argentina	MERVAL	02/01/1992–31/05/2016
BGR	Bulgaria	SOFIX	20/10/2000–31/05/2016
BRA	Brazil	Bovespa Index	11/01/1995–31/05/2016
CHL	Chile	IPSA	02/01/1995–31/05/2016
CHN	China	SSE Composite Index	19/12/1990–31/05/2016
COL	Colombia	IGBC	03/07/2001–31/05/2016
HRV	Croatia	CROBEX	02/07/1997–31/05/2016
IDN	Indonesia	IDX Composite	02/01/1987–31/05/2016
IND	India	BSE Sensex	03/04/1979–31/05/2016
MEX	Mexico	Mexico IPC	04/01/1989–31/05/2016
MYS	Malaysia	FTSE Bursa Malaysia KLCI	02/01/1980–31/05/2016
PAK	Pakistan	KSE 100 Index	29/06/1989–31/05/2016
PER	Peru	S&P/BVL Peru General Index	02/01/1992–31/05/2016
PHL	Philippines	PSEi	02/01/1986–31/05/2016
POL	Poland	WIG 20	02/01/1995–31/05/2016
RUS	Russia	RTS Index	01/09/1995–17/12/2015
SAU	Saudi Arabia	TASI	19/10/1998–31/05/2016
ZAF	South Africa	FTSE/JSE All-Share Index	30/06/1995–31/05/2016

Table 3 (continued)

This table reports the three-letter country abbreviations according to ISO norms, the national stock market indices, and the sample periods for all 23 developed countries (panel A) and 18 emerging markets (panel B), respectively

trading could be problematic for earlier time periods when trading volume used to be lower (e.g., Lo and Wang 2000) or for less liquid markets in the sample.[21]

To mitigate concerns of overestimated trading performance, we use the common approach of delaying the actual entry into a position by one day after a signal is triggered (see, e.g., Bessembinder and Chan 1995; Ready 2002; Sullivan et al. 1999). More specifically, if a technical signal is generated on day t, it is utilized at the close price of day $t + 1$. Since order imbalances and partial adjustments of stale prices tend to normalize after one trading day, it is assumed that the close of the following day is the first trading opportunity for investors. Also, assuming that stock prices are equally likely to trade at the bid or the ask price one day after a trade signal occurs, delayed trading corrects for spread-induced trading costs.[22]

6 In-sample results

6.1 Performance of technical trading rules

In this section, we present the results of the application of the Stepwise Superior Predictive Ability Test. While we examine subperiods and the impact of transaction costs in later sections, the following analysis addresses full sample periods of all 41 market indices under the assumption that trading is free of any costs.

The results are reported in Table 5, where panel A shows the results for developed countries and panel B shows the results for emerging markets, respectively. The column "Full sam." lists the number of technical trading rules with superior performance against buying and holding the index (i.e., these rules exhibit a p-value of less than 0.1 according to the Stepwise Superior Predictive Ability Test based on the Sharpe ratio criterion). We find that 13 of the 23 developed market indices and 14 of the 18 emerging market indices are predictable with at least one technical trading rule. The highest degree of predictability among developed country indices in terms of the total number of rules with superior performance is observed for Hong Kong (290 or about 4.5% of all considered heuristics), Portugal (153 or about 2.4%), and Great Britain (101 or about 1.6%). Among the emerging market indices, predictability is highest for Peru (1700 or about 26.5%), Pakistan (805 or about 12.6%), and Bulgaria (556 or about 8.7%). Thus, while the share of predictable markets is not only higher among the sample of emerging market indices, these markets also

[21] Previous research suggests that, in particular, emerging equity markets are characterized by rather low trading volume and nonsynchronous prices (e.g., AlKhazali 2011; Camilleri and Green 2014).

[22] For example, Gatev et al. (2006) postpone trades of a pairs trading strategy by one trading day to reduce the risk of upward biased returns caused by potentially high bid–ask spreads on signal days.

Table 4 Descriptive statistics

Market	Ann. returns (%)		Daily returns (%)					Annual inflation rates (%)			
	Mean	Std. dev.	Min.	P5	Median	P95	Max.	Mean	Min.	Median	Max.
	Panel A: Developed countries										
AUS	6.36	15.78	−28.71	−1.45	0.05	1.39	6.07	3.40	−0.55	2.57	9.26
AUT	3.83	21.22	−10.25	−2.12	−0.01	1.91	12.02	1.96	0.26	0.81	3.64
BEL	3.26	18.20	−8.32	−1.88	0.00	1.69	9.33	1.83	0.48	0.82	3.99
CAD	5.30	14.50	−11.79	−1.35	0.02	1.28	9.37	3.74	−2.31	3.17	11.09
CHE	5.85	18.19	−11.11	−1.74	0.03	1.66	10.79	1.07	−1.20	1.57	5.41
DEU	5.70	19.39	−13.71	−1.85	0.01	1.82	10.80	2.55	−0.49	1.92	7.62
DNK	8.03	18.57	−11.72	−1.86	0.01	1.81	9.50	4.56	0.25	3.63	13.36
ESP	4.45	22.09	−13.19	−2.22	0.02	2.11	13.48	3.28	−0.22	2.34	7.33
FIN	6.82	25.50	−17.40	−2.48	0.00	2.43	14.56	2.26	−0.08	1.86	7.68
FRA	3.60	22.01	−10.14	−2.19	0.00	2.07	10.59	1.59	0.07	0.84	3.29
GBR	7.81	14.89	−11.38	−1.45	0.06	1.33	7.46	3.22	−0.07	2.51	11.27
GRC	2.23	29.65	−17.71	−2.89	0.00	2.90	13.75	3.07	−1.97	3.41	11.18
HKG	10.17	28.41	−40.54	−2.58	0.02	2.57	17.25	5.19	−6.01	5.32	17.76
ISR	11.39	22.99	−11.72	−2.26	−0.00	2.21	10.35	6.21	−0.31	5.41	16.88
ITA	−1.95	25.01	−13.33	−2.61	0.01	2.44	10.88	1.91	0.44	0.81	3.27
JPN	7.53	18.97	−16.14	−1.84	0.00	1.81	13.23	2.70	−1.90	4.68	22.97
KOR	7.97	23.73	−17.37	−2.24	0.00	2.32	11.28	7.34	−1.23	7.63	30.60
NLD	6.62	21.02	−12.78	−2.01	0.03	1.88	11.18	1.62	−1.05	1.12	4.18
NOR	6.50	23.78	−24.00	−2.21	0.02	2.18	11.12	3.52	−5.21	4.28	15.39
PRT	1.76	18.46	−10.38	−1.86	0.00	1.77	10.20	2.82	−0.39	1.90	7.38
SGP	1.71	18.42	−8.70	−1.79	0.00	1.77	7.53	0.93	−3.58	2.44	5.92
SWE	8.66	22.76	−8.80	−2.28	0.02	2.17	11.02	2.74	0.33	2.45	9.47
USA	7.29	15.44	−22.90	−1.45	0.05	1.44	10.96	3.20	−0.32	2.33	9.46
	Panel B: Emerging markets										
ARG	24.08	44.22	−75.71	−3.95	0.10	3.98	29.02	14.01	−3.56	13.16	41.12
BGR	9.25	24.17	−20.90	−1.94	−0.01	2.01	21.07	4.41	−0.67	3.12	11.08
BRA	33.36	36.92	−17.21	−3.33	0.11	3.56	28.83	8.43	4.92	2.89	18.46
CHL	14.33	17.67	−7.67	−1.60	0.10	1.80	11.80	5.07	−0.05	3.15	12.16
CHN	13.10	37.20	−17.91	−2.97	0.01	2.92	71.92	5.01	−1.26	5.18	20.62
COL	14.73	20.22	−11.05	−1.86	0.03	1.88	14.69	4.98	1.91	1.82	7.68
HVR	4.28	24.03	−13.38	−2.04	0.00	2.08	17.47	2.95	−0.10	1.86	6.01
IDN	5.53	19.77	−13.96	−1.82	0.02	1.76	9.73	12.33	2.44	12.80	75.27
IND	14.02	24.42	−13.66	−2.29	0.05	2.46	18.90	7.62	2.28	3.01	15.73
MEX	20.79	24.06	−14.31	−2.20	0.03	2.35	12.15	12.33	1.53	10.56	38.46
MYS	5.52	20.96	−24.15	−1.72	0.00	1.76	20.82	3.37	−8.72	3.84	10.39
PAK	14.94	22.48	−13.21	−2.26	0.00	2.24	12.76	10.00	0.40	7.20	38.51
PER	24.02	23.34	−13.29	−2.00	0.01	2.34	12.82	9.28	0.11	15.96	69.26
PHL	13.01	25.37	−15.79	−2.25	0.01	2.37	16.18	6.51	−0.72	4.61	22.38
POL	8.07	22.80	−10.29	−2.25	0.00	2.27	7.89	5.39	0.30	6.76	27.94
RUS	10.40	40.62	−21.20	−3.88	0.02	3.78	20.20	17.55	1.97	15.66	72.39

Table 4 (continued)

Market	Ann. returns (%)		Daily returns (%)					Annual inflation rates (%)			
	Mean	Std. dev.	Min.	P5	Median	P95	Max.	Mean	Min.	Median	Max.
SAU	8.07	23.28	−11.68	−2.21	0.05	1.93	16.40	4.62	−16.91	10.58	20.15
ZAF	10.92	19.15	−12.69	−1.85	0.03	1.83	7.42	7.32	5.17	1.73	12.21

This table reports descriptive statistics for the 23 developed and the 18 emerging market indices (panel A and panel B). Ann. returns (%) shows the mean and standard deviation (std. dev.) of unadjusted daily log returns in percent that are annualized with a factor of 252 and $\sqrt{252}$, respectively. Daily returns (%) reports the minimum (min.), 5th percentile (P5), median, 95th percentile (P95), and maximum (max.) daily log return in percent. Annual inflation rates (%) provides the mean, minimum, median, and maximum annual inflation rate in percent

exhibit a higher degree of predictability in terms of the proportion of rules with superior performance. For instance, 8 of the 13 predictable developed market indices have at most 14 outperforming rules, which corresponds to only about 0.2% of the full universe of considered technical trading rules.

This first analysis suggests that the majority of markets are predictable with technical rules, and, in particular, several emerging markets have a significant proportion of rules with superior performance. On the one hand, the high number of predictive rules in emerging markets may be due to lower market efficiency, as the stock markets of less developed countries tend to incorporate new information into prices more slowly and lack institutional framework to enhance efficiency (see, e.g., Araújo Lima and Tabak 2004; Bhuyan et al. 2008; Poshakwale 2002; Sharma and Thaker 2015). On the other hand, trading in these markets tends to incur comparatively high transaction costs (Lesmond 2005), which may then be picked up as profits through active trading strategies under a zero-trading cost scheme.[23] In fact, most technical trading rules generate trading signals very frequently, such that these rules would incur substantial transaction costs if applied to real markets. Later robustness checks will assess the sensitivity of performance to transaction costs.

Since investors usually strive for maximum profits, the best-performing technical trading rules play an important role among the whole set of examined rules. Therefore, Table 5 also reports basic characteristics for these specific rules for all markets.[24] For 23 (15) markets, support and resistance rules (moving average rules)

[23] According to Grossman and Stiglitz (1980), capital markets cannot be perfectly information efficient because a compensation for the costs associated with trading and obtaining information is necessary to encourage participation. Otherwise, there would be no incentive to trade. These costs may vary strongly across the markets in our sample.

[24] Note that the summary statistics for time invested, mean return per trade, fraction of winners, number of trades per year, and mean holding period in Table 5 are not computed based on the double-or-out strategy (which is, however, used to calculate the performance measure) to give an "undistorted" view on the performance of the rules. For example, under the double-or-out scheme, short signals require a market-neutral position and result in returns of zero (or the risk-free rate), leading to statistics that are meaningless for evaluating the actual trading characteristics of technical trading rules.

Table 5 Outperforming technical trading rules

Market	Full sam.	Best-performing trading rules												
	Outperf. rules	Best rule	Perf. measure	*p*-Val.	Ann. ex. ret	Time inv. (%)	Mean ret./trade (%)		Fraction of winners (%)		Number of trades/year		Mean holding period	
							Lo.	Sh.	Lo.	Sh.	Lo.	Sh.	Lo.	Sh.
	Panel A: Developed countries													
AUS	0	FR(0.1, 0, 0.075, 0)	0.478	0.312	10.18	84.8	3.20	1.29	70.5	49.2	2.4	1.8	49.7	50.0
AUT	10	SR(0, 200, 0, 0, 25)	0.651*	0.056	3.70	91.3	5.43	−0.79	83.3	29.4	4.8	4.5	25.0	25.0
BEL	0	SR(0, 100, 0, 0, 50)	0.409	0.542	2.54	95.3	5.41	−1.59	82.4	35.7	2.6	2.5	50.0	50.0
CAD	14	MA(100, 1, 0, 0, 0)	0.492**	0.018	10.26	99.2	1.76	0.58	42.6	31.6	4.4	4.4	35.4	21.7
CHE	0	SR(0, 100, 0, 2, 50)	0.417	0.870	0.67	96.7	5.60	−5.84	75.0	16.7	2.6	2.4	50.0	50.0
DEU	1	SR(0, 3, 0.05, 0, 50)	0.270*	0.088	4.20	34.2	4.43	1.50	73.3	47.5	0.6	1.1	50.0	50.0
DNK	0	MA(150, 5, 0.001, 0, 0)	0.449	0.150	13.97	95.1	10.93	2.83	50.0	32.1	1.0	1.0	158.5	77.5
ESP	0	SR(0, 200, 0, 0, 10)	0.521	0.732	2.52	92.0	1.56	−0.37	78.0	15.0	11.9	11.3	10.0	10.0
FIN	11	MA(30, 25, 0.005, 0, 0)	0.497**	0.044	18.27	97.2	3.73	1.21	64.3	46.3	3.8	3.5	30.6	24.0
FRA	0	SR(0, 4, 0.02, 0, 50)	0.357	0.272	6.31	50.2	5.32	1.48	90.0	48.2	0.7	1.9	50.0	50.0
GBR	101	SR(0, 10, 0.001, 0, 0)	0.804***	0.008	5.59	77.0	0.32	0.12	54.6	29.0	13.0	11.4	3.0	13.6
GRC	35	SR(0, 50, 0.01, 0, 0)	0.895**	0.026	13.75	84.9	1.14	2.25	55.1	25.9	2.1	2.0	52.9	50.2
HKG	290	MA(10, 1, 0, 0, 0)	0.661***	< 0.001	25.93	99.9	1.04	0.45	47.7	38.1	17.4	17.4	8.1	6.4
ISR	1	CB(20, 0.1, 0, 10)	0.305*	0.050	10.85	55.8	1.06	0.27	64.9	50.3	9.0	5.1	10.0	10.0
ITA	0	SR(0, 25, 0, 2, 25)	0.733	0.468	8.98	99.2	2.49	6.19	72.7	36.8	5.1	5.0	25.0	25.0
JPN	59	SR(0, 10, 0.02, 0, 0)	0.452***	0.002	2.88	47.9	0.54	0.23	63.5	34.2	3.0	5.3	21.4	21.3
KOR	1	MA(20, 15, 0.005, 0, 0)	0.379*	0.096	13.10	75.0	2.66	0.25	59.4	42.7	4.5	4.8	23.4	17.7
NLD	0	SR(0, 10, 0, 3, 5)	0.475	0.240	4.34	99.4	0.51	−0.02	64.9	44.8	25.2	24.9	5.0	5.0
NOR	1	MA(25, 1, 0, 0, 0)	0.470*	0.050	15.45	99.7	1.01	0.42	46.8	32.4	10.8	10.8	14.0	9.2
PRT	153	SR(0, 200, 0.03, 0, 0)	1.294**	0.014	7.95	76.4	8.42	8.00	47.8	26.1	0.4	0.4	200.6	201.6
SGP	0	SR(0, 10, 0.01, 0, 50)	0.701	0.284	11.19	51.1	6.96	3.70	88.9	58.3	0.5	2.1	50.0	50.0

Table 5 (continued)

Market	Full sam.	Best-performing trading rules												
	Outperf. rules	Best rule	Perf. measure	*p*-Val.	Ann. ex. ret	Time inv. (%)	Mean ret./trade (%)		Fraction of winners (%)		Number of trades/year		Mean holding period	
							Lo.	Sh.	Lo.	Sh.	Lo.	Sh.	Lo.	Sh.
SWE	0	MA(125, 5, 0, 0, 0)	0.353	0.228	12.05	98.4	5.21	1.16	41.7	30.5	1.9	1.9	85.5	46.0
USA	2	MA(200, 1, 0, 0, 0)	0.221*	0.058	6.81	98.8	2.34	−0.04	46.9	26.2	3.0	2.9	58.7	25.6
	Panel B: Emerging markets													
ARG	0	CB(25, 0.15, 0.02, 50)	0.296	0.230	21.40	60.9	9.70	1.41	64.9	53.6	2.1	1.0	50.0	50.0
BGR	556	MA(50, 1, 0, 2, 0)	1.056***	0.006	35.13	90.6	5.90	3.97	48.2	44.3	3.4	3.7	36.6	27.4
BRA	86	SR(15, 0, 0.05, 0, 0)	0.522**	0.020	34.38	57.3	13.56	1.88	57.7	48.8	2.3	1.8	41.3	27.8
CHL	30	MA(25, 1, 0, 0, 0)	0.608***	0.002	18.96	99.6	1.84	0.27	41.1	37.2	9.0	9.0	16.2	11.7
CHN	70	MA(20, 1, 0, 0, 0)	0.601**	0.014	38.24	99.7	2.51	1.32	43.2	42.8	10.0	10.0	13.2	12.0
COL	20	MA(5, 1, 0, 0, 0)	0.777**	0.014	25.92	99.9	0.57	0.15	51.4	44.8	35.8	35.8	4.3	2.7
HRV	5	SR(0, 50, 0.005, 0, 0)	0.826**	0.032	8.96	84.0	1.73	1.47	54.0	28.7	1.9	1.8	52.7	50.6
IDN	0	SR(0, 200, 0.02, 0, 0)	0.566	0.108	0.47	76.3	0.13	0.15	47.4	14.8	1.2	1.0	92.6	94.8
IND	1	MA(20, 1, 0, 0, 0)	0.324*	0.064	16.75	99.8	1.37	0.12	45.3	36.1	11.2	11.2	12.7	9.7
MEX	12	SR(10, 0, 0, 5, 50)	0.352**	0.028	18.52	95.3	6.51	0.42	75.3	47.9	2.7	1.6	50.0	50.0
MYS	366	MA(50, 1, 0.001, 0, 0)	0.819***	< 0.001	20.37	91.5	2.81	2.44	41.3	40.1	4.1	3.6	33.4	25.9
PAK	805	SR(0, 25, 0.015, 0, 0)	1.031***	< 0.001	14.22	72.1	1.38	1.70	62.4	38.9	2.3	2.0	43.4	40.5
PER	1700	SR(0, 20, 0.005, 0, 0)	1.115***	< 0.001	17.51	80.7	1.66	0.51	60.8	27.6	4.6	3.4	33.4	27.1
PHL	35	MA(20, 1, 0, 0, 0)	0.619**	0.012	25.49	99.7	1.80	0.59	44.2	36.6	10.7	10.6	13.3	10.3
POL	0	SR(0, 25, 0, 5, 10)	0.480	0.190	6.41	98.6	2.17	−0.39	68.0	29.4	3.4	2.3	10.0	10.0
RUS	4	SR(10, 0, 0, 0, 0)	0.714*	0.097	41.20	99.7	4.12	2.43	47.8	43.4	10.3	10.3	22.5	17.5
SAU	34	SR(0, 20, 0.001, 0, 0)	1.121***	0.008	13.45	79.0	0.64	0.79	60.5	25.8	4.9	4.2	23.0	20.3
ZAF	0	SR(0, 25, 0.001, 5, 0)	0.361	0.788	2.96	55.3	0.94	0.07	56.4	45.5	2.5	8.7	10.4	13.2

Table 5 (continued)

This table reports the number of outperforming trading rules as well as basic characteristics of best-performing trading rules for each of the 23 developed countries (panel A) and the 18 emerging markets (panel B). Full sam. reports the number of outperforming technical trading rules (outperf. rules) identified by the Stepwise Superior Predictive Ability Test using the whole universe of considered technical trading rules. A rule is regarded as "outperforming" if the estimated performance measure is associated with a p-value of less than 0.1. Best-performing trading rules shows basic characteristics for the technical trading rule with the highest performance in terms of the Sharpe ratio criterion. These rules do not necessarily have to show significant outperformance. The abbreviations for the technical rules and their parameters, which are displayed in the column "Best rule," are defined in Table 1. A parameter value of 0 indicates that the corresponding parameter is not applicable. Perf. measure is the performance measure computed as the difference between the Sharpe ratio of the best trading rule and the Sharpe ratio of the buy-and-hold benchmark strategy annualized with a factor of $\sqrt{252}$ (cf., equation (3)). p-Val. is the p-value obtained from the Stepwise Superior Predictive Ability Test to indicate the statistical significance of the estimated performance measure of the best-performing trading rule. Ann. ex. ret. is the annualized return of the best trading rule in excess of the annualized benchmark return (both in percent). Time inv. (%) is the percentage of time the best trading rule is either long or short in the respective index. Mean ret./trade (%) reports the mean return per long (Lo.) and short (Sh.) trade of the best trading rule in percent. Fraction of winners (%) reports the percentage of long and short trades with a positive return generated by the best trading rule. Number of trades/year reports the mean number of long and short trades per year of the best trading rule. Mean holding period reports the mean number of days a long or short position is held when trading the best trading rule. While Perf. measure and Ann. exc. ret. result from the actual double-or-out strategy applied to mitigate short positions, the remainder of characteristics reported for best trading rules are based on the assumption that long (short) positions are associated with a purchase (sale) of one unit of the respective index. The superscripts ∗∗∗, ∗∗, and ∗ indicate the significance levels of $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively

have the best performance in terms of the Sharpe ratio criterion.[25] Moreover, the best-performing rules have significant excess Sharpe ratios of up to 1.29 (Portugal) for developed markets and 1.12 (Saudi Arabia) for emerging markets. These rules, furthermore, produce highly economically significant excess returns, which mainly range from more than 10% to around 40% per year.

Table 5 also shows that best-performing rules predominately exhibit long or short exposure to the market [i.e., 28 (39) of the 41 best rules are either long or short at least 80% (50%) of the time]. In several cases, the best rules are never market-neutral once an initial trading signal is triggered, as a signal converts a long position to a short position and vice versa (e.g., this is the case for all moving average rules without trading filters). For both developed and emerging market indices, best-performing trading rules tend to generate higher average returns per trade than short positions, and long signals are more likely to generate winning trades. This is in line with previous research by, for instance, Brock et al. (1992) who report that gains of long–short trading strategies are mainly driven by long positions, which is consistent with generally upward-trending equity markets in the long run.

The average number of transactions per year varies significantly among best rules. Many of them, however, generate trading signals very frequently. For example, the best rule for the Colombian market is a 5 day moving average that emits more than 70 trades per year on average with a mean holding period of just 4.3 days on the long side and 2.7 days on the short side. Accordingly, trading such rules may accumulate high transaction costs.

In the next two sections, we check for the robustness of our in-sample results by examining how the predictive ability of technical trading rules evolves over time, using subperiods of the full sample periods. Thereafter, we explore the impact of transaction costs.

6.2 Subperiod analysis

In a further step, we test whether the results for the full sample periods also hold during subperiods of 7 years.[26] Table 6 presents the results for developed country indices (panel A) and emerging market indices (panel B). Again, outperforming rules are defined as those rules that have a *p*-value of less than 0.1 according to the Stepwise Superior Predictive Ability Test using the Sharpe ratio criterion. For comparison purposes, we report the number of rules with superior performance over the entire sample periods, as already presented in Table 5, in the last column of the table.

[25] This finding is similar to other studies on technical analysis. Sullivan et al. (1999) use an identical set of rules except for relative strength index rules and find that a 5 day moving average exhibits the highest Sharpe ratio based on daily market data of the DJIA. Similarly, Bajgrowicz and Scaillet (2012) report that moving averages and support and resistance rules perform best for the DJIA in several subperiods during 1897 and 2011. Hsu et al. (2010) analyze the predictive ability of 30 currency pairs and find that moving average heuristics perform the best in most cases.

[26] The length of the subperiods does not significantly affect the overall results. We choose intervals of 7 years to have at least two subperiods per country of approximately equal length and to obtain samples that contain enough observations to have meaningful test power.

For 20 of the 23 indices for which we find outperforming rules in at least one subperiod, the highest number of outperforming rules is observed in the first subperiod. In these cases, the proportion of predictive rules tends to decrease sharply after the first subperiods. Most notably, there are 350 outperforming rules for the Finnish stock market index between 1988 and 1994, 305 outperforming rules for the Bulgarian stock market index between 2002 and 2008, and 103 outperforming rules for the Brazilian stock market index between 1995 and 2001. While these are the results for the first subperiods, for all heuristics in the sample, the three indices become unpredictable during the subsequent subperiods. A decline in technical trading performance over time is also found by Kish and Kwon (2002) and LeBaron (2000) for major US stock indices and by Hsu et al. (2016), Neely et al. (2009), and Olsen (2004) for several foreign exchange pairs. Our results, furthermore, show that predictive power drops much earlier in developed markets than in emerging markets. In developed markets, predictive ability of technical trading rules disappears almost completely by the early 2000s. For emerging markets, the sharpest decline in predictability is observed between the penultimate (2002–2008) and the most recent (2009–2016) subperiods in terms of the share of predictable markets (see also the last row of the panel). In the last subperiod, no developed market index is predictable anymore and only two emerging market indices are still predictable with only one rule each.

There are several potential reasons for this negative trend in predictability. As discussed in the previous section, trade-intensive rules may perform particularly well before transaction costs. As trading costs have steadily declined in recent decades (e.g., Jones 2002), rules that earn high profits by exploiting a zero-cost system should, all else equal, be more successful during the early subperiods. Another explanation for our results is different levels of market efficiency over time, which is in line with the adaptive market hypothesis of Lo (2004). According to that, the first subperiods can be interpreted as "early evolutionary stages," which are subject to greater market efficiency in the future, for instance, through gradual learning by market participants. Thus, technical trading strategies can generate superior performance over certain periods, and the more proprietary these strategies are, the longer they may yield attractive results. However, even very sophisticated trading strategies may eventually "die out" if market conditions change significantly, such as more intense competition among traders for strategy returns (Timmermann 2008; Timmermann and Granger 2004).[27] Closely related to the notion of growing market efficiency is the rise of institutional investors and

[27] Moreover, the adaptive market hypothesis allows for cases in which markets can go through cycles of varying efficiency as well as changes in the structure and intensity of competition among market participants (Lo 2004). This may be one reason for the rare cases in which the number of outperforming rules rises again after a previous decline (e.g., the number of outperforming rules for Japan's Nikkei drops to zero between 1960 and 1966 and then rises again to 18 in the subsequent subperiod).

Table 6 Outperforming technical trading rules during subperiods

Market	Number of outperforming rules									
	1953–1959	1960–1966	1967–1973	1974–1980	1981–1987	1988–1994	1995–2001	2002–2008	2009–2016	Full sample
	Panel A: Developed countries									
AUS	–	–	–	–	–	0	0	0	0	0
AUT	–	–	–	–	–	46	0	1	0	10
BEL	–	–	–	–	–	–	0	0	0	0
CAD	–	–	–	8	0	0	0	0	0	14
CHE	–	–	–	–	–	–	0	0	0	0
DEU	–	–	0	0	0	0	0	0	0	1
DNK	–	–	–	–	–	–	0	0	0	0
ESP	–	–	–	–	–	0	0	0	0	0
FIN	–	–	–	–	–	350	0	0	0	11
FRA	–	–	–	–	–	0	0	0	0	0
GBR	–	–	–	–	–	434	69	0	0	101
GRC	–	–	–	–	–	–	2	0	0	35
HKG	–	–	–	323	10	0	0	0	0	290
ISR	–	–	–	–	–	0	0	0	0	1
ITA	–	–	–	–	–	–	–	0	0	0
JPN	84	0	18	0	0	0	0	0	0	59
KOR	–	–	–	–	0	0	0	0	0	1
NLD	–	–	–	–	–	0	0	0	0	0
NOR	–	–	–	–	–	0	0	0	0	1
PRT	–	–	–	–	–	–	23	33	0	153
SGP	–	–	–	–	–	–	–	0	0	0
SWE	–	–	–	–	–	0	0	0	0	0
USA	0	1	0	0	0	0	0	0	0	2
Frac. pos.	50.0%	50.0%	33.3%	40.0%	16.7%	18.8%	14.3%	8.7%	0.0%	56.5%

Table 6 (continued)

Market	Number of outperforming rules									
	1953–1959	1960–1966	1967–1973	1974–1980	1981–1987	1988–1994	1995–2001	2002–2008	2009–2016	Full sample
	Panel B: Emerging markets									
ARG	–	–	–	–	–	–	0	0	0	0
BGR	–	–	–	–	–	–	–	305	0	556
BRA	–	–	–	–	–	–	103	0	0	86
CHL	–	–	–	–	–	–	13	1	0	30
CHN	–	–	–	–	–	–	24	0	0	70
COL	–	–	–	–	–	–	–	25	0	20
HRV	–	–	–	–	–	–	–	1	0	5
IDN	–	–	–	–	–	2	0	0	0	0
IND	–	–	–	–	0	0	0	0	0	1
MEX	–	–	–	–	–	–	0	0	0	12
MYS	–	–	–	–	29	0	1	0	0	366
PAK	–	–	–	–	–	–	246	126	0	805
PER	–	–	–	–	–	–	480	661	1	1700
PHL	–	–	–	–	–	1	0	0	1	35
POL	–	–	–	–	–	–	0	0	0	0
RUS	–	–	–	–	–	–	–	4	0	4
SAU	–	–	–	–	–	–	–	48	0	34
ZAF	–	–	–	–	–	–	–	1	0	0
Frac. pos.	–	–	–	–	50.0%	50.0%	50.0%	50.0%	11.1%	77.8%

This table reports the number of outperforming trading rules for subperiods of the 23 developed market indices (panel A) and the 18 emerging market indices (panel B). Trading rules are classified as "outperforming" if they exhibit a *p*-value of, at most, 0.1 according to the Stepwise Superior Predictive Ability Test for the Sharpe ratio criterion. For comparison reasons, Full sample shows the number of outperforming rules identified over the full sample period as reported in Table 5 as well. Frac. pos. reports the fraction of markets with a positive number of outperforming rules during a specific (sub)period for both developed and emerging markets, respectively. Dashes indicate that complete data were not available for the respective markets and subperiods

professional algorithmic traders.[28] While institutional investors are not necessarily the better investors, greater competition among these investors can lead to an increase in know-how about trading techniques and drive the speed of processing market data.

In summary, the declining performance of technical trading rules across markets may not be surprising, as the rules studied in this paper are considered quite simple and were not ahead of their time at the beginning of the sample periods. The ease with which these naive technical trading rules can be copied suggests that initially predictive rules may become unfavorable relatively quickly. While at least some of the trading rules have performed significantly better than buy-and-hold strategies under a zero-transaction cost scheme in early subperiods, they all appear to be useless in current markets.

6.3 Transaction cost analysis

In the previous analyses, transaction costs were not taken into account. The superior performance found for several technical trading heuristics does not necessarily imply superior returns after transaction costs, since a zero-cost scheme is prone to overestimate the performance of highly trade-intensive heuristics. Transaction costs may also vary substantially across the examined markets (Lesmond 2005). In the following, we relax the strong simplification of trading without costs.

A proper transaction cost analysis is not trivial since reliable cost estimates for certain markets and time periods are usually not available. Therefore, a common approach in the literature is to calculate break-even transaction costs of the rules with superior performance at zero transaction costs (see, e.g., Bessembinder and Chan 1995, 1998; Hsu et al. 2016). For example, Hsu et al. (2016) simply calculate the break-even costs for the best trading rules they identified in a previous test for superior predictive ability. The drawback of this approach is that it does not reveal the maximum transaction cost per trade up to which a trading rule still exhibits statistically significant outperformance. In addition, technical trading rules that emit frequent signals are likely to be more sensitive to transaction costs compared with other rules. Thus, the distribution of rules with significant performance is most likely affected by the introduction or increase of transaction costs (see also Bajgrowicz and Scaillet 2012). To address these issues, we consider transaction costs before testing for statistical significance.

Our approach is simple, but to the best of our knowledge has not been used in the literature before. We increase the transaction costs in steps of five basis points and use the Stepwise Superior Predictive Ability Test at each transaction cost level

[28] Friedman (1996) reports that the share of institutional investors in the USA increased from 10% in 1950 to about 50% in 1990. Gompers and Metrick (2001) show that the share of large institutional investors in the stock market almost doubled between 1980 and 1996. More recently, high-frequency trading has captured a significant share of trading volume. Kaya (2016) reports that the share of high-frequency trading in the European stock market surged from nearly 0% in 2005 to over 50% in 2010. During the same period, high-frequency trading accounted for about 20% and more than 50% of the trading volume in the US stock market.

to test whether technical trading rules have superior performance. As a result, we obtain the number of outperforming rules for each transaction cost level. Once the transaction costs have reached a level where no significant performance can be detected, the algorithm stops.

Table 7 reports the results of the transaction cost study (the results for zero transaction costs from Table 6 are also reported for ease of comparison). Regarding panel A for developed countries, for 10 of the 23 market indices (i.e., Canada, Finland, Great Britain, Greece, Hong Kong, Israel, Japan, Norway, Portugal, and the USA) at least one trading rule with significant outperformance at positive transaction costs exists. However, for these markets, the number of outperforming rules and the maximum level of transaction costs are mostly small. Trading rules with superior performance at transaction costs of more than ten basis points are only found in five markets. The highest single-trip transaction costs of 200 basis points are estimated for one rule in the Japanese stock market. This is followed by the stock indices from Hong Kong and Portugal, both of which are predictable with one rule for costs of up to 40 basis points per transaction. Of the 18 emerging markets, 11 markets (i.e., Bulgaria, Chile, China, Colombia, Croatia, Malaysia, Pakistan, Peru, the Philippines, Russia, and Saudi Arabia) are predictable for positive one-way transaction costs of at least five basis points (see panel B). The Bulgarian, Malaysian, Pakistani, and Peruvian stock market indices have the highest predictability for costs of at least 50 basis points per trade. With 112 outperforming rules at the 500 basis point level and four outperforming rules at the 1000 basis point level, the Bulgarian SOFIX exhibits the highest predictability. With a few exceptions, our results are consistent with previous findings in the literature that technical trading performance is quickly offset by moderate transaction costs (e.g., Allen and Karjalainen 1999; Bajgrowicz and Scaillet 2012; Ready 2002).

The impact of transaction costs for the full sample of technical trading rules is also shown in Fig. 1 for the US S&P 500 (panel A) and the Peruvian S&P/PVL Peru General (panel B) as examples for a developed and an emerging market, respectively.[29] Both panels plot the Sharpe ratio performance measure for all 6406 technical heuristics at transaction costs of 0 and 25 basis points per transaction. Generally, the impact of transaction costs is quite significant for rules that favor very frequent trading (these are often rules with lower parameter values which are mainly shown further to the left for each of the five classes of heuristics). For example, while the performance measures of all moving average rules before transaction costs range within the interval of $[-0.5, 0.3]$ in the US market, performance suffers significantly when trading costs are added. With single-trip costs of 25 basis points, excess Sharpe ratios of moving average rules are as low as -3.5. Despite the meaningful impact of trading costs on performance, the example of the Peruvian market suggests that a large fraction of rules generate excess Sharpe ratios well above zero, which is not the case in the US market. Again, the higher degree of predictability of the Peruvian market could be due to relatively lower market efficiency and generally higher transaction costs required to trade in this market in reality.

[29] We choose the US market due to the longest available sample period and as it is the most investigated market in the literature. The Peruvian index is an example of a market that is predictable by comparatively many rules for both zero and moderate transaction costs.

Table 7 Outperforming technical trading rules and transaction costs

Market	Single-trip transaction costs (basis points)																
	0	5	10	15	20	25	30	40	50	75	100	150	200	300	400	500	1000
	Panel A: Developed countries																
AUS	0																
AUT	10																
BEL	0																
CAD	14	3	1														
CHE	0																
DEU	1																
DNK	0																
ESP	0																
FIN	11	7	2														
FRA	0																
GBR	101	5															
GRC	35	18	6	5	3	1	1										
HKG	290	164	123	57	38	22	8	1									
ISR	1	1															
ITA	0																
JPN	59	16	7	4	2	2	1	1	1	1	1	1	1				
KOR	1																
NLD	0																
NOR	1	1															
PRT	153	74	47	18	14	7	3	1									
SGP	0																
SWE	0																
USA	2	1	1	1	1	1	1										

Table 7 (continued)

Market	Single-trip transaction costs (basis points)																
	0	5	10	15	20	25	30	40	50	75	100	150	200	300	400	500	1000
	Panel B: Emerging markets																
ARG	0																
BGR	556	465	449	352	335	331	267	195	170	169	159	148	145	144	142	112	4
BRA	86																
CHL	30	2	1														
CHN	70	25	2	2													
COL	20	4	4	1													
HRV	5	1															
IDN	0																
IND	1																
MEX	12																
MYS	366	19	17	14	10	7	5	3	1								
PAK	805	620	504	421	339	265	195	114	54	1	1						
PER	1700	1498	1367	1129	1054	953	833	692	611	397	289	43	5	5			
PHL	35	18	2	1													
POL	0																
RUS	4	1															
SAU	34	6	1														
ZAF	0																

This table reports the number of outperforming technical trading rules at various single-trip transaction cost levels for developed countries (panel A) and emerging markets (panel B). Trading rules are classified as "predictive" if they exhibit a *p*-value of at most 0.1 according to the Stepwise Superior Predictive Ability Test

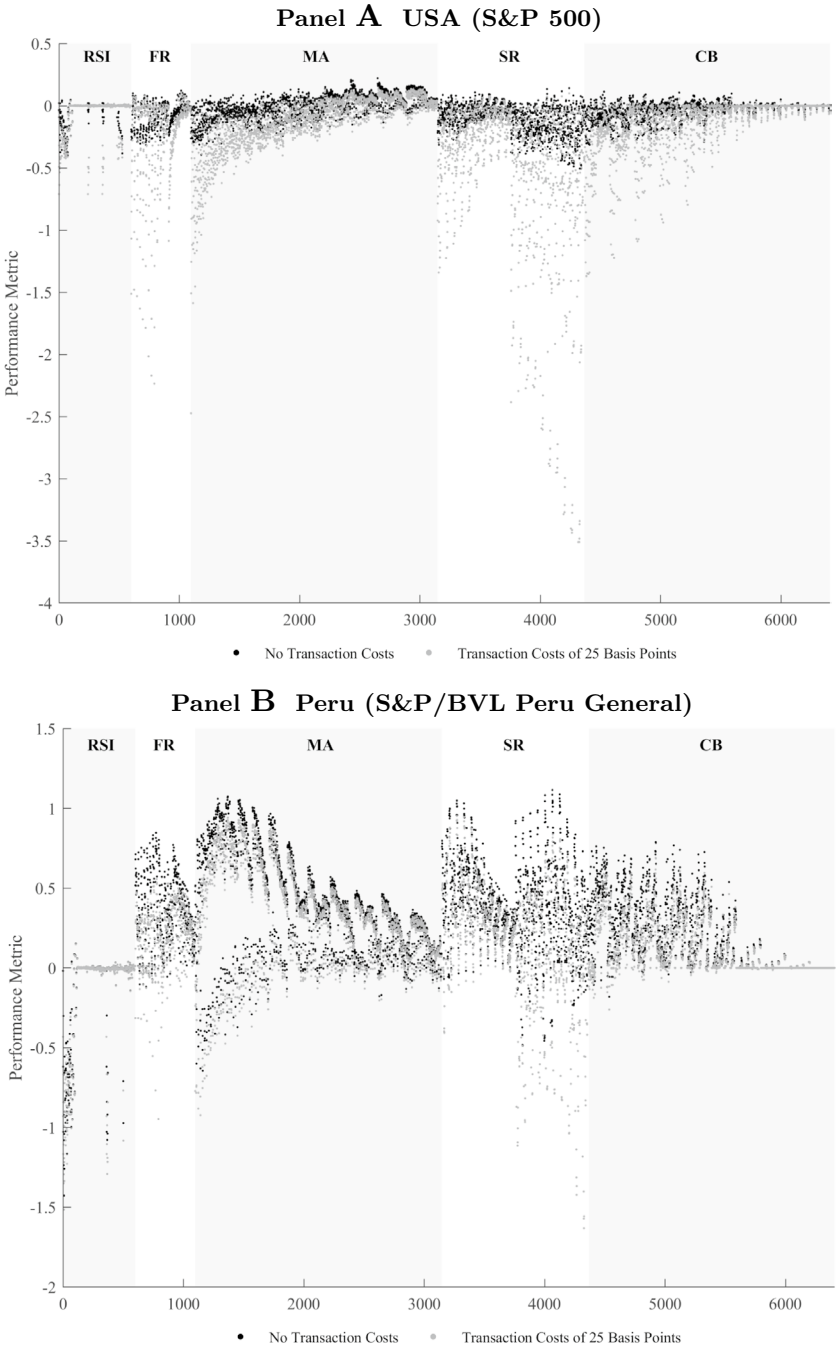
Fig. 1 Trading costs and the performance of technical trading rules. This figure shows the performance of all 6406 technical trading rules for the USA (panel A) and Peru (panel B) as representatives for the sample of developed countries and emerging markets, respectively. A heuristic's performance measure is the difference between its Sharpe ratio and the Sharpe ratio of a buy-and-hold benchmark annualized with a factor of $\sqrt{252}$ [cf., Eq. (3)]. Vertical axes represent the indices of technical heuristics. The five heuristic classes are highlighted with alternating gray and white areas, where RSI are relative strength index rules, FR are filter rules, MA are moving average rules, SR are support and resistance rules, and CB are channel breakout rules, respectively. Black (gray) dots indicate the performance measures of technical trading rules based on single-trip transaction costs of 0 (25) basis points ▶

In most markets, the estimated maximum transaction costs for a single transaction are small compared with what traders would likely have had to pay to trade these markets during the sample periods. For example, Chan and Lakonishok (1993) estimate single-trip trading costs of 14 basis points incurred by institutional traders for large US stocks between 1986 and 1988. According to Stoll and Whaley (1983), average trading costs were much higher in the preceding decades. Moreover, the emerging markets in our sample are likely to have much higher transaction costs. For the period from 1991 to 2000, Lesmond (2005) estimates variable trade costs of 0.5–1.0% for Malaysia, 0.6–0.9% for Poland (both depending on order volume), 0.8–1.05% for China, 1.5% for the Philippines (both for foreign investors), and 1.0% for Indonesia. Given these figures, our analysis casts doubt on whether markets could have been traded profitably with any of the investigated trading rules.

Next, we investigate the evolution of the average number of trades and average holding periods of outperforming rules at different transaction cost levels. Table 8 presents the relative change in the average number of trades for positive transaction costs.[30] For each market and transaction cost level, we average the number of trades for all rules with superior performance. To ensure comparability across markets, we normalize the average values for each transaction cost level of a market with the corresponding value when transaction costs are zero. Thus, the table shows changes in the average number of trades relative to the zero-transaction cost scenario (e.g., a value of 0.9 implies a 10% decrease in the average number of trades among all outperforming rules at a given transaction cost level compared with the corresponding average number of trades of all outperforming rules at zero transaction costs). The results indicate that the average number of trades decreases in transaction costs for most developed and emerging markets. Thus, as conjectured above, the share of outperforming rules with frequent trading signals declines for higher transaction costs. Table 9 presents the results for the average holding period conditional on transaction costs. The reported figures are calculated analogously to those presented in Table 8. According to that, in almost all markets, the average holding periods increase monotonically with transaction costs compared to the case of zero transaction costs.

The results from Tables 8 and 9 suggest that the share of outperforming rules with infrequent trading signals and longer average holding periods tends to increase as

[30] For clarity, the table only reports results for markets that have at least one rule with statistically significant performance at least at the 10% level for single-trip transaction costs of five basis points, as presented in Table 7.



transaction costs rise. Based on that, one may expect relatively more outperforming rules which mimic a simple buy-and-hold strategy when transaction costs are high.

Table 8 Development of the average number of trades

Market	Single-trip transaction costs (in basis points)															
	5	10	15	20	25	30	40	50	75	100	150	200	300	400	500	1000
	Panel A: Developed countries															
CAD	1.08	1.01														
FIN	0.82	0.50														
GBR	0.98															
GRC	0.82	0.70	0.55	0.52	0.28	0.28										
HKG	0.48	0.27	0.18	0.17	0.17	0.18	0.10									
ISR	0.61															
JPN	0.75	0.90	0.88	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87				
NOR	1.00															
PRT	0.49	0.45	0.31	0.30	0.29	0.30	0.30									
USA	0.99	0.99	0.99	0.99	0.99	0.99										
	Panel B: Emerging markets															
BGR	0.97	0.87	0.97	0.87	0.85	0.54	0.35	0.39	0.34	0.34	0.34	0.31	0.30	0.28	0.24	0.11
CHL	0.67	0.85														
CHN	0.50	0.27	0.39													
COL	0.61	0.48	0.72													
HRV	0.96															
MYS	0.68	0.43	0.41	0.40	0.40	0.39	0.40	0.33								
PAK	1.03	1.05	1.11	1.21	1.20	1.10	1.05	0.70	0.21	0.11						
PER	0.91	0.90	0.88	0.87	0.79	0.70	0.60	0.61	0.59	0.47	0.43	0.36	0.23			
PHL	0.57	0.85	0.37													
RUS	0.48															
SAU	1.21	0.12														

This table reports the average number of trades of outperforming trading rules at various single-trip transaction cost levels in developed countries (panel A) and emerging markets (panel B) relative to the base case of zero transaction costs. For reasons of clarity, only markets with at least one technical rule with significant outperformance at single-trip transaction costs of five basis points are considered (cf., Table 7). The number of trades are averaged for all outperforming rules at each transaction cost level and normalized by the corresponding average number of trades of outperforming rules from the scenario with transaction costs of zero

Table 9 Development of the average holding periods

Market	Single-trip transaction costs (in basis points)															
	5	10	15	20	25	30	40	50	75	100	150	200	300	400	500	1000
	Panel A: Developed countries															
CAD	1.09	1.09														
FIN	1.00	0.99														
GBR	1.03															
GRC	1.01	1.03	1.05	1.05	1.05	1.05										
HKG	1.12	1.15	1.18	1.20	1.21	1.21	1.21									
ISR	1.08															
JPN	1.12	1.17	1.17	1.17	1.17	1.17	1.17	1.17	1.17	1.17	1.17	1.17				
NOR	1.06															
PRT	1.12	1.17	1.18	1.19	1.19	1.19	1.19									
USA	1.00	1.00	1.00	1.00	1.00	1.00										
	Panel B: Emerging markets															
BGR	1.15	1.25	1.34	1.43	1.48	1.55	1.64	1.73	1.76	1.77	1.79	1.79	1.80	1.92	1.92	2.27
CHL	1.05	1.05														
CHN	1.12	1.13	1.14													
COL	1.01	1.13	1.13													
HRV	1.03															
MYS	1.13	1.20	1.21	1.22	1.24	1.25	1.25	1.25								
PAK	1.10	1.14	1.22	1.25	1.28	1.30	1.31	1.32	1.32	1.41						
PER	1.12	1.23	1.34	1.41	1.46	1.57	1.65	1.67	1.70	1.81	1.82	1.98	2.02			
PHL	1.32	1.35	1.38													
RUS	1.13															
SAU	1.06	1.12														

This table reports the average holding periods of outperforming trading rules at various single-trip transaction cost levels in developed countries (panel A) and emerging markets (panel B) relative to the base case of zero transaction costs. Only markets with at least one technical rule with significant outperformance at single-trip transaction costs of five basis points are considered (cf., Table 7). The holding periods are averaged for all outperforming rules at each transaction cost level and normalized by the corresponding average holding period of outperforming rules from the scenario with transaction costs of zero

However, this is not the case. Despite the longer average holding periods, we observe a decrease in the average time invested in 17 of the 21 markets for increasing transaction costs. Thus, the outperforming rules tend to exploit very specific price patterns and have longer periods with no exposure to the market when transaction costs are high.

7 Out-of-sample results

In this section, we address two fundamental problems that arise in analyses of technical trading rules over long sample periods. First, using technical trading rules requires active trading, and technical analysis has been shown to be used by amateur and professional investors who deliberately engage in active portfolio management (e.g., Faugère et al. 2013, Lease et al. 1980). Thus, the common convention in the literature of testing trading rules over periods of several decades most often diverges from the short-term oriented trading behavior of individuals who may aim to apply heuristics which they find most valuable at a given point in time. Second, backtests (such as those conducted in this paper so far) only provide ex-post information on whether trading rules could have been traded profitably. However, in-sample outperformance does not imply out-of-sample outperformance, nor does it give any indication of how to select the best rules to trade in the future. So far, we cannot answer the question whether a trader could have exploited the predictability of some of the investigated markets (at least if trading were free or very cheap) by implementing a profitable trading system based on the studied technical rules. We approach this task by performing an out-of-sample persistence analysis of technical trading performance in the following.

To test out-of-sample performance, we mimic the trading activities of a technical trader, similar to Bajgrowicz and Scaillet (2012). For each market, we divide the sample periods into 36 month subperiods and select the trading rules with the best performance in terms of the highest excess Sharpe ratio (we refer to these 36 month intervals in which in-sample performance of technical trading rules is evaluated as "testing periods").[31] The best-performing rule during a testing period is used for trading during the subsequent 36 month period (which we refer to as "trading period"). When a trading signal is generated by the selected rule during a trading period, the index is purchased. A potentially open position is automatically closed at the end of a trading period. We apply the double-or-out strategy as in the previous analyses to mitigate true short positions.

Table 10 presents the results based on single-trip transaction costs of 0, 10, 25, and 50 basis points.[32] The reported performance measure is the difference between annualized Sharpe ratios for technical trading returns and the corresponding

[31] To check for robustness, we also employ excess raw returns as a second performance measure. The corresponding results are discussed later.

[32] These transaction cost estimates are similar to the values considered in previous studies. Allen and Karjalainen (1999), for example, also use 10, 25, and 50 basis points to evaluate the impact of transaction costs on the performance of technical trading rules applied to the S&P 500 between 1928 and 1995. Ready (2002) uses single-trip trading costs of 13 basis points for the DJIA between 1962 and 1999, and Bajgrowicz and Scaillet (2012) study the DJIA for single-trip trading costs of 12.5 basis points for the period from 1897 to 2011.

buy-and-hold benchmark returns. In addition to the out-of-sample performance, the table also reports the corresponding in-sample performance for each transaction cost level (i.e., the in-sample results are based on the best rules identified during the testing periods, which are used to evaluate the out-of-sample performance during subsequent trading periods). The statistical significance of the performance is evaluated using a hypothesis test proposed by Bailey and López de Prado (2012), which assesses the null hypothesis that two Sharpe ratios (computed from potentially non-normal return distributions) are equal.

The analysis shows that the in-sample performance is sizable (with excess Sharpe ratios mostly above 1) and highly statistically significant even at single-trip transaction costs of 50 basis points. This may not be surprising since in-sample performance is by construction the result of extensive data snooping. More importantly, the out-of-sample performance is mostly insignificant or negative and significant. For higher single-trip transaction costs of 25 and 50 basis points, we observe significant out-of-sample underperformance in 14 and 18 markets, respectively, at least at the 10% significance level. The findings imply that best-performing technical trading rules do not generate persistent performance over relatively short time horizons, and that such a trading system is detrimental compared with simply buying and holding the respective market index. This impression is confirmed in panel C of Table 10, which reports results for equally weighted portfolios of developed market indices, emerging market indices, and all market indices, respectively. All in-sample performance measures are positive and statistically significant at the 1% level for the four transaction cost scenarios. In contrast, the out-of-sample performance measures are insignificant for single-trip costs of 0 basis points and turn negative and significant at positive transaction costs in most of the considered cases [e.g., for single-trip costs of 50 basis points, the performance measure equals − 0.315 (significant at the 5% level) for the developed markets portfolio as well as − 0.507 and − 0.385 for the emerging markets and all-markets portfolio (both significant at the 1% level)]. We reestimate the selection algorithm using excess raw returns as an alternative performance measure. The results presented in Table 11 in the appendix confirm our baseline findings obtained with the Sharpe ratio criterion.

Panels A–C in Fig. 2 plot the performance of the three portfolios over the entire sample period for single-trip transaction costs of 0 and 25 basis points. Here, performance is measured as the in-sample and out-of-sample excess returns (i.e., the daily differences between the equally weighted returns from technical trading and the equally weighted returns from the buy-and-hold benchmark strategy). All three panels show that the in-sample excess returns are substantial and comparatively unaffected by transaction costs. In contrast, out-of-sample performance is regressive most of the time, and all portfolios generate negative returns over the full sample period, even in the absence of transaction costs.

In summary, the results presented in this section demonstrate that past superior performance of technical trading rules does not persist in the near future. This seriously calls into question whether the studied rules could have been traded at any profit. Based on our simple selection algorithm for trading rules, technical trading is harmful for investment performance across the broad range of considered markets. Our results corroborate those of Bajgrowicz and Scaillet (2012), who also measure very poor out-of-sample performance of simple technical trading rules applied to the DIJA.

Table 10 Persistence of performance

Market	Single-trip transaction costs															
	0 Basis points				10 Basis points				25 Basis points				50 Basis points			
	In-sample		Out-of-sample		In-sample		Out-of-sample		In-sample		Out-of-sample		In-sample		Out-of-sample	
	Perf	*p*-Val	Perf	*p*-Val	Perf	*p*-Val	Perf	*p*-Val	Perf	*p*-Val	Perf	*p*-Val	Perf	*p*-Val	Perf	*p*-Val
	Panel A: Developed countries															
AUS	1.535***	< 0.001	− 0.094	0.352	1.419***	< 0.001	−0.184	0.245	1.286***	< 0.001	− 0.074	0.369	1.155***	< 0.001	− 0.169	0.264
AUT	1.841***	< 0.001	0.253	0.162	1.739***	< 0.001	0.169	0.266	1.651***	< 0.001	0.154	0.286	1.505***	< 0.001	0.159	0.279
BEL	1.665***	< 0.001	0.106	0.348	1.595***	< 0.001	0.060	0.382	1.498***	< 0.001	0.039	0.392	1.361***	< 0.001	−0.174	0.276
CAD	1.503***	< 0.001	− 0.384**	0.013	1.413***	< 0.001	− 0.555***	< 0.001	1.291***	< 0.001	− 0.609***	< 0.001	1.078***	< 0.001	− 0.572***	< 0.001
CHE	1.403***	< 0.001	− 0.424**	0.038	1.315***	< 0.001	− 0.367*	0.069	1.230***	< 0.001	− 0.373*	0.065	1.128***	< 0.001	− 0.334*	0.094
DEU	1.332***	< 0.001	− 0.310**	0.036	1.247***	< 0.001	− 0.365**	0.014	1.151***	< 0.001	− 0.307**	0.037	1.054***	< 0.001	− 0.276*	0.059
DNK	1.427***	< 0.001	− 0.054	0.385	1.322***	< 0.001	− 0.670	0.378	0.957***	< 0.001	− 0.263	0.175	0.904***	< 0.001	− 0.323	0.113
ESP	1.625***	< 0.001	− 0.056	0.381	1.560***	< 0.001	− 0.080	0.366	1.553***	< 0.001	0.142	0.302	1.416***	< 0.001	0.183	0.252
FIN	1.607***	< 0.001	− 0.266	0.151	1.582***	< 0.001	− 0.207	0.222	1.513***	< 0.001	− 0.221	0.205	1.360***	< 0.001	− 0.438**	0.027
FRA	1.406***	< 0.001	− 0.186	0.250	1.310***	< 0.001	− 0.239	0.185	1.199***	< 0.001	− 0.406**	0.043	0.823***	< 0.001	− 0.467**	0.021
GBR	1.956***	< 0.001	0.429**	0.033	1.828***	< 0.001	0.047	0.387	1.660***	< 0.001	−0.118	0.329	1.568***	< 0.001	− 0.408**	0.037
GRC	1.916***	< 0.001	0.354*	0.080	1.881***	< 0.001	0.323	0.105	1.836***	< 0.001	0.350*	0.083	1.745***	< 0.001	0.088	0.361
HKG	1.601***	< 0.001	− 0.057	0.371	1.526***	< 0.001	−0.112	0.302	1.405***	< 0.001	−0.186	0.184	1.319***	< 0.001	− 0.260*	0.087
ISR	1.188***	< 0.001	− 0.135	0.310	1.158***	< 0.001	− 0.252	0.167	1.051***	< 0.001	− 0.357*	0.069	0.841***	< 0.001	−0.206	0.226
ITA	1.687***	< 0.001	− 0.047	0.392	1.600***	< 0.001	−0.287	0.200	1.525***	< 0.001	−0.318	0.170	1.468***	< 0.001	−0.328	0.162
JPN	1.629***	< 0.001	0.172	0.157	1.425***	< 0.001	0.130	0.232	1.332***	< 0.001	0.072	0.338	1.186***	< 0.001	−0.075	0.332
KOR	1.464***	< 0.001	− 0.144	0.263	1.349***	< 0.001	−0.129	0.285	1.305***	< 0.001	−0.141	0.268	1.024***	< 0.001	−0.327**	0.047
NLD	1.534***	< 0.001	0.170	0.256	1.328***	< 0.001	0.105	0.336	1.262***	< 0.001	− 0.089	0.352	1.178***	< 0.001	− 0.220	0.186
NOR	1.518***	< 0.001	0.042	0.389	1.423***	< 0.001	−0.034	0.393	1.312***	< 0.001	− 0.354*	0.070	1.215***	< 0.001	− 0.438**	0.027
PRT	2.108***	< 0.001	1.176***	< 0.001	2.008***	< 0.001	1.124***	< 0.001	1.913***	< 0.001	0.967***	< 0.001	1.785***	< 0.001	0.226	0.234

Table 10 (continued)

Market	Single-trip transaction costs													
	0 Basis points				10 Basis points				25 Basis points				50 Basis points			
	In-sample		Out-of-sample		In-sample		Out-of-sample		In-sample		Out-of-sample		In-sample		Out-of-sample	
	Perf	*p*-Val	Perf	*p*-Val	Perf	*p*-Val	Perf	*p*-Val	Perf	*p*-Val	Perf	*p*-Val	Perf	*p*-Val	Perf	*p*-Val
SGP	1.530***	< 0.001	0.106	0.368	1.432***	< 0.001	0.027	0.397	1.273***	< 0.001	−0.223	0.279	1.191***	< 0.001	−0.323	0.188
SWE	1.365***	< 0.001	− 0.066	0.375	1.350***	< 0.001	−0.104	0.341	1.160***	< 0.001	− 0.193	0.234	1.010***	< 0.001	− 0.231	0.186
USA	1.262***	< 0.001	− 0.312**	0.018	1.187***	< 0.001	− 0.389***	0.003	1.090***	< 0.001	− 0.280**	0.033	0.997***	< 0.001	−0.329**	0.013
	Panel B: Emerging markets															
ARG	0.999***	< 0.001	− 0.303	0.132	0.917***	< 0.001	− 0.274	0.161	0.819***	< 0.001	− 0.348*	0.091	0.787***	< 0.001	− 0.295	0.138
BGR	1.634***	< 0.001	0.196	0.309	1.625***	< 0.001	0.347	0.171	1.607***	< 0.001	0.089	0.379	1.544***	< 0.001	− 0.014	0.399
BRA	1.179***	< 0.001	− 0.150	0.319	1.156***	< 0.001	− 0.179	0.291	1.118***	< 0.001	−0.213	0.255	1.067***	< 0.001	− 0.262	0.202
CHL	1.513***	< 0.001	0.040	0.391	1.441***	< 0.001	− 0.242	0.195	1.342***	< 0.001	− 0.397*	0.058	1.164***	< 0.001	− 0.327	0.108
CHN	1.745***	< 0.001	0.123	0.334	1.676***	< 0.001	0.210	0.236	1.584***	< 0.001	0.135	0.323	1.536***	< 0.001	− 0.088	0.365
COL	1.667***	< 0.001	− 0.415	0.137	1.623***	< 0.001	− 0.461	0.107	1.571***	< 0.001	− 0.530*	0.070	1.054***	< 0.001	−0.276*	0.059
HRV	1.833***	< 0.001	0.312	0.183	1.780***	< 0.001	0.348	0.160	1.477***	< 0.001	0.219	0.270	1.370***	< 0.001	0.214	0.270
IDN	1.748***	< 0.001	− 0.072	0.372	1.665***	< 0.001	− 0.138	0.307	1.619***	< 0.001	− 0.015	0.398	1.476***	< 0.001	− 0.027	0.395
IND	1.193***	< 0.001	− 0.398**	0.024	1.117***	< 0.001	− 0.487***	0.006	1.051***	< 0.001	− 0.476***	0.007	0.991***	< 0.001	− 0.379**	0.031
MEX	1.218***	< 0.001	− 0.766***	< 0.001	1.180***	< 0.001	− 0.755***	< 0.001	1.103***	< 0.001	− 0.818***	< 0.001	1.024***	< 0.001	− 0.810***	< 0.001
MYS	1.893***	< 0.001	− 0.097	0.340	1.807***	< 0.001	− 0.005	0.400	1.741***	< 0.001	0.038	0.389	1.592***	< 0.001	− 0.140	0.284
PAK	2.072***	< 0.001	0.209	0.241	1.990***	< 0.001	0.042	0.391	1.856***	< 0.001	− 0.133	0.324	1.726***	< 0.001	− 0.431***	0.041
PER	1.806***	< 0.001	0.303	0.143	1.685***	< 0.001	0.174	0.283	1.623***	< 0.001	− 0.017	0.398	1.529***	< 0.001	− 0.112	0.345
PHL	1.413***	< 0.001	− 0.223	0.197	1.685***	< 0.001	− 0.305	0.107	1.308***	< 0.001	− 0.346*	0.073	1.285***	< 0.001	− 0.348*	0.071
POL	1.188***	< 0.001	− 0.049	0.390	1.103***	< 0.001	− 0.140	0.331	1.618***	< 0.001	− 0.295	0.173	0.885***	< 0.001	− 0.473**	0.046
RUS	1.710***	< 0.001	− 0.173	0.303	1.650***	< 0.001	− 0.341	0.136	1.618***	< 0.001	− 0.371	0.112	1.564***	< 0.001	− 0.421*	0.078

Table 10 (continued)

Market	Single-trip transaction costs													
	0 Basis points				10 Basis points				25 Basis points				50 Basis points			
	In-sample		Out-of-sample		In-sample		Out-of-sample		In-sample		Out-of-sample		In-sample		Out-of-sample	
	Perf	*p*-Val	Perf	*p*-Val	Perf	*p*-Val	Perf	*p*-Val	Perf	*p*-Val	Perf	*p*-Val	Perf	*p*-Val	Perf	*p*-Val
SAU	2.072***	< 0.001	− 0.235	0.263	2.027***	< 0.001	− 0.162	0.328	1.865***	< 0.001	− 0.387	0.125	1.801***	< 0.001	− 0.370	0.134
ZAF	1.431***	< 0.001	− 0.384	0.101	1.316***	< 0.001	− 0.542**	0.026	1.211***	< 0.001	− 0.557**	0.022	1.039***	< 0.001	− 0.395*	0.093
	Panel C: Equally weighted portfolios															
Dev	3.262***	< 0.001	− 0.044	0.375	2.965***	< 0.001	− 0.132	0.228	2.672***	< 0.001	− 0.182	0.138	2.422***	< 0.001	− 0.315**	0.016
Emg	3.372***	< 0.001	− 0.196	0.203	3.412***	< 0.001	− 0.359**	0.041	3.232***	< 0.001	− 0.456**	0.010	3.120***	< 0.001	− 0.507***	0.004
All	3.696***	< 0.001	− 0.006	0.399	3.369***	< 0.001	− 0.195	0.118	3.034***	< 0.001	− 0.261**	0.045	2.744***	< 0.001	− 0.385***	0.003

This table reports results for the in-sample and out-of-sample performance of best trading rules for single-trip transaction costs of 0, 10, 25, and 50 basis points. Panel A and panel B show results for developed countries and emerging markets, and panel C shows results for equally weighted portfolios of developed (Dev), emerging (Emg), and all market indices (All). Perf is the performance measure computed as the difference between annualized Sharpe ratios for technical trading returns and buy-and-hold benchmark returns. *p*-Val denotes the *p*-value obtained from a statistical test with the null hypothesis that the performance measure is equal to zero (see Bailey and López de Prado 2012). The superscripts ***, **, and * indicate the significance levels of $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively

8 Conclusions

This paper provides a comprehensive analysis of a broad universe of simple technical trading rules applied to a total of 23 developed market indices and 18 emerging market indices using the Stepwise Superior Predictive Ability Test. The novelty of this test is its ability to identify the whole subset of trading rules with superior performance relative to a buy-and-hold benchmark, while accounting for data snooping bias. To the best of our knowledge, we are the first to apply this powerful statistical test to a large set of trading rules in a comparative analysis of multiple stock markets.

Our in-sample results show that technical trading rules have predictive power in some markets during relatively early periods when transaction costs are ignored. However, in recent years, the investigated technical rules do not have predictive power anymore. To evaluate the impact of transaction costs, we run a stepwise algorithm to determine the number of outperforming trading rules for different transaction cost levels. This analysis reveals a high sensitivity of trading performance to moderate single-trip transaction costs. Moreover, an out-of-sample analysis suggests that the performance of the best technical heuristics is generally not persistent over shorter time periods in the future. These in-sample best trading rules tend to significantly underperform out-of-sample even when transaction costs are low.

The existing literature on the profitability of technical trading rules is relatively comprehensive, but it shows inconclusive results and relies mainly on limited data or outdated statistical tests. We provide extensive empirical evidence that simple technical rules do not achieve data snooping-free outperformance of various stock indices. This is true even for markets that are considered far less information efficient than the extensively studied US stock market. Overall, our results cast doubt on the economic value of technical trading rules that have been found to generate superior performance by several previous studies based on tests with less statistical rigor. The results strongly suggest that the investigated trading signals are noise and that a trading strategy which follows these signals ultimately underperforms the market due to an accumulation of transaction costs.

Our analysis is limited with respect to several dimensions, so the results of this study should not be generalized beyond the scope of the trading rules and data examined in this paper. Clearly, the examined rules represent only a subset of the potentially testable technical trading rules and are among the simplest used in practice. There are several, more subtle technical strategies that are not part of the universe tested in this paper. Moreover, the analysis is limited to daily close prices of national stock market indices and does not provide evidence for more detailed data such as intraday stock prices. The boom in high-frequency algorithmic trading in recent years, driven by increasing computational capabilities, may have created highly specialized investors who generate excess returns through technical trading. More recent empirical evidence related to this subject by Batten et al. (2015) and Gebka et al. (2014) point in this direction. However, the nature, complexity, and trading horizon of these technical approaches drastically differ from the naive heuristics typically employed by individual investors.

Fig. 2 In-sample and out-of-sample performance of technical trading rules. This figure displays the development of the in-sample and out-of-sample performance of technical trading rules for equally weighted portfolios of developed country indices (panel A), emerging market indices (panel B), and all market indices (panel C), respectively. Performance is measured as the returns generated from technical trading in excess of buy-and-hold returns form the corresponding stock index in percent. Solid black (solid gray) lines show the development of in-sample excess returns based on single-trip transaction costs of 0 (25) basis points. Dashed black (dashed gray) lines show the development of out-of-sample excess returns based on single-trip transaction costs of 0 (25) basis points ▶

Despite the poor performance of simple technical rules, they are still widely used by market participants. Future research should investigate whether there may be other, nonmonetary factors that motivate these investors to apply technical analysis. Potential preference-based reasons for trading technical signals and the behavior of technical traders have hardly been addressed in the finance literature.

Appendix 1: Implementation of the stepwise superior predictive ability test

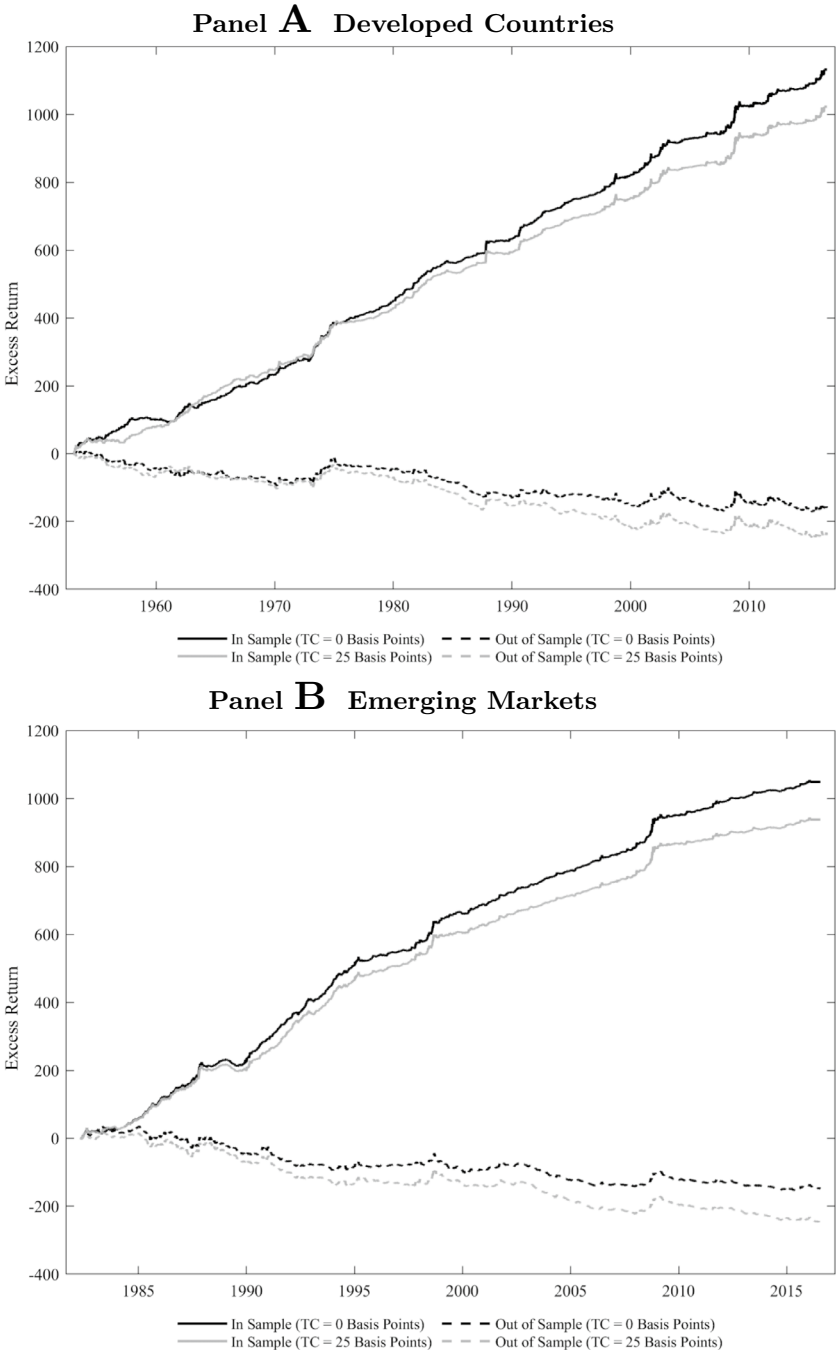
In this paper, the objective is to test whether trading according to signals of m technical trading rules outperforms a buy-and-hold strategy. Performance is measured in terms of the Sharpe ratio, such that the performance measure for a trading rule k is defined as $\theta_k = \left(\bar{\pi}_k - \bar{r}^f\right)/\hat{\sigma}_k - \left(\bar{r} - \bar{r}^f\right)/\hat{\sigma}_0$ (cf., equation (3)). We use the Stepwise Superior Predictive Ability Test introduced by Hsu et al. (2010) to obtain p-values and control for data snooping bias.

Hsu et al. (2010) employ the stationary bootstrap by Politis and Romano (1994) to resample original time series. We outline the general procedure of the bootstrap using the matrix $\Pi = \left(\pi_{t,k}\right)_{\substack{t=1,\dots,N \\ k=1,\dots,m}}$ of strategy returns. The indices of each vector $\pi_k = (\pi_{1,k}, \pi_{2,k}, \dots, \pi_{N,k})'$ are resampled yielding a pseudo-time series $\pi_k^b \equiv \pi_k(n_{t,b})$ for the b-th bootstrap sample, $b = 1, \dots, B$. The indices $n_{t,b}$ result from resampling the original time indices $1, \dots, N$ in blocks of stochastic lengths, where the block lengths follows a geometric distribution with parameter $q \in (0, 1]$. Due to the properties of the geometric distribution, blocks have an expected length of $1/q$. The resampling of blocks is implemented with two $N \times B$ random matrices with independent entries $u_{t,b}, v_{t,b} \sim \text{unif}(0, 1]$. The indices are initialized by setting

$$n_{1,b} = \lceil N u_{1,b} \rceil, \tag{4}$$

where $\lceil \cdot \rceil$ is the ceiling function that rounds its argument to the nearest integer towards infinity. The indices for $t = 2, \dots, N$ are then determined by

$$n_{t,b} = \begin{cases} \lceil N u_{t,b} \rceil, & v_{t,b} < q, \\ \mathbb{1}\{n_{t-1,b} < N\} n_{t-1,b} + 1, & v_{t,b} \geq q, \end{cases} \tag{5}$$



where $\mathbb{1}\{\cdot\}$ is the indicator function. Thus, resampled indices are determined recursively, where the realization of the random variable $v_{t,b}$ relative to q

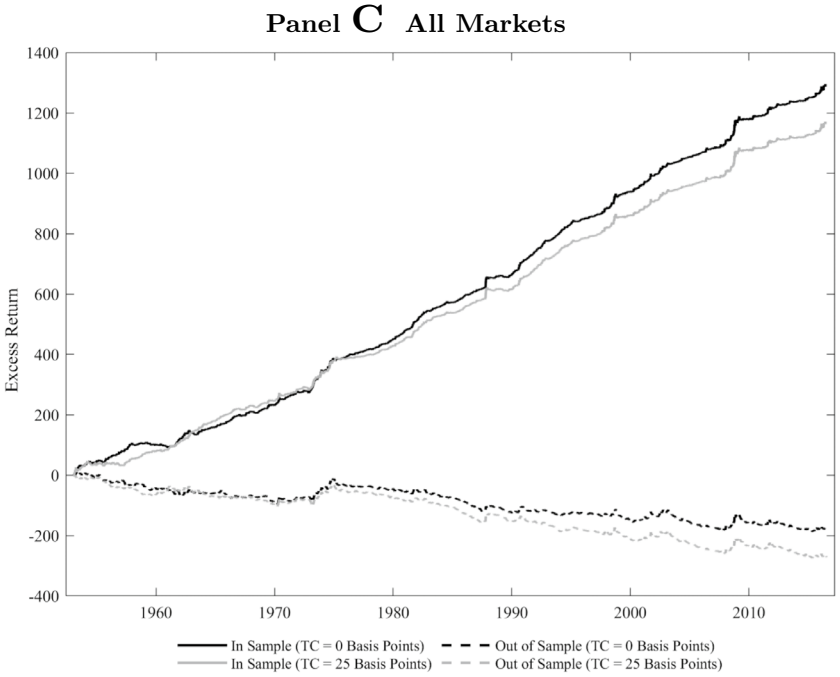


Fig. 2 (continued)

determines whether a new block is started, and the start index of a block is determined by the random variable $u_{t,b}$. Finally, we obtain B bootstrapped matrices, $\Pi^b = \left(\pi_1^b, \pi_2^b, \ldots, \pi_m^b\right)$, $b = 1, \ldots, B$, by using the b-th resample of indices to reorder all columns of Π.

The stationary bootstrap is jointly applied to the time series of trading returns, the risk-free rate, and the benchmark returns, so that we can compute bootstrapped versions of θ_k of the form

$$\theta_k^b = \frac{\bar{\pi}_k^b - \bar{r}^{fb}}{\hat{\sigma}_k^b} - \frac{\bar{r}^b - \bar{r}^{fb}}{\hat{\sigma}_0^b}, \tag{6}$$

where $\hat{\sigma}_k^b$ and $\hat{\sigma}_0^b$ are the standard deviations of resampled strategy returns and benchmark returns based on bootstrap sample b using the bootstrapped variance estimator of Politis and Romano (1994).[33] This finally yields B vectors of bootstrapped performance measures, $\theta^b = \left(\theta_1^b, \theta_2^b, \ldots, \theta_m^b\right)$.

To implement the stepwise procedure, the elements of the vector of original performance measures, $\theta = (\theta_1, \theta_2, \ldots, \theta_m)$, are sorted in descending order. Let, moreover, j and m_j denote the step of the stepwise test and the number of rejections of the null

[33] Politis and Romano (1994) compute the variance estimator, $\hat{\sigma}_k^2$, for model k as $\hat{\sigma}_k^2 = \hat{\gamma}_{0,k} + 2\sum_{i=1}^{N-i} \omega_{n,i}\hat{\gamma}_{i,k}$ with kernel weights under the stationary bootstrap given by $\omega_{n,i} = \frac{N-i}{N}(1-q)^i + \frac{i}{N}(1-q)^{N-i}$, where q is the parameter of the geometric distribution, and with the empirical covariance $\hat{\gamma}_{i,k} = N^{-1}\sum_{j=1}^{N-i}\left(\pi_{j,k} - \bar{\pi}_k\right)\left(\pi_{j+i,k} - \bar{\pi}_k\right)$.

hypothesis (i.e., the number of models with true outperformance) at step j. To initialize the first step, let $j = 1$ and $m_0 = 0$. We compute an empirical null distribution $\{\phi_j^b\}_{b=1,\ldots,B}$, where

$$\phi_j^b = \sqrt{N} \max_{k=m_{j-1}+1,\ldots,m} \{\theta_k^b - \theta_k + \hat{\mu}_k\} \tag{7}$$

with

$$\hat{\mu}_k = \theta_k \mathbb{1}\left\{ \frac{\sqrt{N}\theta_k}{\hat{\sigma}_k} \leq -\sqrt{2 \log \log N} \right\}. \tag{8}$$

Expression (8) formulates a measure to recenter the bootstrapped distribution for models performing particularly bad.[34] We use $\{\phi_j^b\}_{b=1,\ldots,B}$ and compute its $(1-\alpha)$ quantile, $q(\alpha)$, with α being the allowed error rate. The subset of models with performance measures satisfying $\sqrt{N}\theta_k > q(\alpha)$, $k = m_{j-1} + 1, \ldots, m$, are recorded as significantly outperforming models. If the number of rejected models at this step, m_j, is zero, the stepwise procedure terminates. Otherwise, if $m_j > 0$, we set $j = j + 1$ and proceed with the next step by recomputing the empirical null distribution based on the new subset of models (i.e., the set of models that does not contain all models that have been identified as outperforming in the previous step).

The number of bootstraps, B, and the parameter of the geometric distribution determining the mean block length, q, are the two exogenous parameters of the stationary bootstrap of Politis and Romano (1994). White (2000) argues that 500 is a sufficiently large number of iterations for the stationary bootstrap. Regarding the parameter of the geometric distribution, Sullivan et al. (1999) show in a sensitivity analysis that the p-values computed with the Reality Check almost do not change if q is set to either 0.01, 0.1, or 0.5, respectively. Similarly, Hsu et al. (2016) also report only negligible sensitivity of results to the choice of bootstrap parameters, and Chen et al. (2009) find that the outcome of the bootstrap procedure is relatively insensitive to the choice of the two parameters. We, therefore, feel safe to set $B = 500$ for the number of bootstrap resamples and $q = 0.1$ as parameter for the geometric distribution in the empirical analysis of this study.

Appendix 2: Definition of trading filters and technical trading rules

Trading filters

Band filters

Band filters specify a multiplicative value, $f_b > 0$, which the price of a security is supposed to additionally exceed after a trading signal has been triggered. Thus, if a

[34] Hansen (2005) shows that poor models are irrelevant for the asymptotic null distribution. However, they cannot be neglected in finite samples as the impact on the distribution of the test statistic of models being little worse than the benchmark may be huge. Therefore, Hansen (2005) does not exclude any models but reduces the influence of the poorest ones. To do so, $-\sqrt{2 \log \log N}$ in expression (8) serves as a threshold and is a result of an application of the law of the iterated logarithm.

technical trading rule generates an unconditional long (short) signal, a long (short) position is only entered when the stock price subsequently increases (decreases) by another $100f_b\%$.

Time-delay filters

Time-delay filters impose a fixed time period, $f_d \in \mathbb{N}$, by which the entry into a position is delayed. Thus, if a trading signal is generated in period t, a position is actually initiated in period $t + f_d$.

Fixed-length filters

Fixed-length filters define a fixed holding period, $f_l \in \mathbb{N}$, after which a position is automatically liquidated. More specifically, a position entered in period t will be liquidated in period $t + f_l$, regardless of intermediate price movements or possible earlier signals. If a trading rule is not supplemented by a fixed-length filter, and unless otherwise specified, a short signal requires both the liquidation of a long position and the entry into a short position, and vice versa.

Technical trading rules

Relative Strength Index The relative strength index, $RSI_t(n)$, in period t is the sum of the upward movements of a security price, P_t, relative to the sum of the upward and absolute downward movements calculated over the last n periods. More formally, we compute the sum of upward and the sum of absolute downward movements as

$$\begin{aligned} U_t(n) &= \sum_{k=1}^{n} \mathbb{1}\{P_{t-k+1} - P_{t-k} > 0\}\big(P_{t-k+1} - P_{t-k}\big), \\ D_t(n) &= -\sum_{k=1}^{n} \mathbb{1}\{P_{t-k+1} - P_{t-k} < 0\}\big(P_{t-k+1} - P_{t-k}\big). \end{aligned} \tag{9}$$

Based on these expressions, the relative strength index is introduced as

$$RSI_t(n) = 100\,\frac{U_t(n)}{U_t(n) + D_t(n)}. \tag{10}$$

Obviously, the RSI ranges from 0 to 100. Securities with extreme high or low relative strength index are considered overbought or oversold, respectively. Following Hsu et al. (2016), we consider a security to be oversold if its $RSI_t(n) \leq 50 - v$, where v is a positive integer, for at least d periods. Then, a long signal is triggered when $RSI_t(n)$ rises above $50 - v$. Short positions are initiated analogously.

Filter rules

The filter rules used by Sullivan et al. (1999) generate an initial long (short) signal as soon as the price of a security rises (falls) by more than $100x\%$. Subsequently, a long position is closed and a short position is entered once the price of the asset falls by at least $100x\%$ from the maximum price that occurred while holding that position. Similarly, a short position is closed and a long position is initiated when the price increases by at least $100x\%$ from the minimum price observed during the holding period.

Let τ denote the period in which the previous trading signal was triggered. A subsequent trading signal is generated in period $t > \tau$ according to the following rules.

$$\begin{aligned}&\text{Long signal in } t:\\ &\left(P_{t-1} < \min\{P_\tau, \ldots, P_{t-2}\}(1+x)\right) \wedge \left(P_t \geq \min\{P_\tau, \ldots, P_{t-1}\}(1+x)\right)\\ &\text{Short signal in } t:\\ &\left(P_{t-1} > \max\{P_\tau, \ldots, P_{t-2}\}(1-x)\right) \wedge \left(P_t \leq \max\{P_\tau, \ldots, P_{t-1}\}(1-x)\right)\end{aligned} \tag{11}$$

We also use an alternative definition for maxima and minima as introduced by Sullivan et al. (1999). According to that, a maximum (minimum) is defined as the most recent price that is higher (lower) than the prices of the previous e periods. This results in the following filter rules.

$$\begin{aligned}&\text{Long signal in } t:\\ &\left(P_{t-1} < P_{\max\limits_{\tilde{t}<t-1}\left\{\tilde{t}\,|\,P_{\tilde{t}} < \min\left\{P_{\tilde{t}-e-1},\ldots,P_{\tilde{t}-2}\right\}\right\}}(1+x)\right)\\ &\quad\wedge\quad \left(P_t \geq P_{\max\limits_{\tilde{t}<t}\left\{\tilde{t}\,|\,P_{\tilde{t}} < \min\left\{P_{\tilde{t}-e},\ldots,P_{\tilde{t}-1}\right\}\right\}}(1+x)\right)\\ &\text{Short signal in } t:\\ &\left(P_{t-1} > P_{\max\limits_{\tilde{t}<t-1}\left\{\tilde{t}\,|\,P_{\tilde{t}} > \max\left\{P_{\tilde{t}-e-1},\ldots,P_{\tilde{t}-2}\right\}\right\}}(1-x)\right)\\ &\quad\wedge\quad \left(P_t \leq P_{\max\limits_{\tilde{t}<t}\left\{\tilde{t}\,|\,P_{\tilde{t}} > \max\left\{P_{\tilde{t}-e},\ldots,P_{\tilde{t}-1}\right\}\right\}}(1-x)\right)\end{aligned} \tag{12}$$

Both definitions of extrema lead to a permanent exposure to the asset as soon as the first trading signal is generated (i.e., there is no possibility for a market-neutral position). A third specification of the filter rules also allows for intermediate neutral positions. This is achieved by different percentage thresholds required to open or close a long or short position. While opening a position still requires a $100x\%$ change in the asset price, closing a long (short) position requires a $100y\%$ move below (above) the previous high (low). Let τ denote the period in which the current position was initiated. The liquidation of this position in period t comes about as follows.

Table 11 Persistence of performance based on excess returns

Market	Single-trip transaction costs															
	0 Basis points				10 Basis points				25 Basis points				50 Basis points			
	In-sample		Out-of-sample		In-Sample		Out-of-sample		In-sample		Out-of-sample		In-sample		Out-of-sample	
	ΔR	*t*-Stat	ΔR	*t*-Stat	ΔR	*t*-Stat	ΔR	*t*-Stat	ΔR	*t*-Stat	ΔR	*t*-Stat	ΔR	*t*-Stat	ΔR	*t*-Stat
	Panel A: Developed countries															
AUS	14.39***	4.14	− 1.93	− 0.52	12.64***	3.66	− 3.00	− 0.76	10.15***	2.99	− 1.50	− 0.38	8.91***	2.63	− 2.80	− 0.71
AUT	23.08***	5.15	2.62	0.52	22.02***	4.90	1.46	0.29	21.42***	4.73	1.73	0.33	20.13***	4.41	1.62	0.31
BEL	14.38***	3.49	0.06	0.01	13.71***	3.33	− 0.54	− 0.12	12.89***	3.12	− 0.79	− 0.17	13.23***	3.13	− 3.49	− 0.74
CAD	11.50***	4.58	− 5.59**	− 1.98	11.36***	4.47	− 8.51***	− 2.58	11.01***	4.27	− 9.43***	− 2.86	8.32***	3.27	− 8.48***	− 2.72
CHE	13.65***	3.37	− 7.72	− 1.53	11.48***	2.88	− 6.55	− 1.44	11.04***	2.75	− 6.59	− 1.49	9.95**	2.48	− 6.08	− 1.36
DEU	14.30***	4.53	− 6.08	− 1.63	12.66***	4.05	− 7.02*	− 1.91	12.31***	3.89	− 6.02*	− 1.69	12.82***	3.93	− 5.51	− 1.52
DNK	9.12**	2.21	− 4.92	− 1.10	7.63*	1.87	− 5.68	− 1.31	7.50*	1.74	− 7.35*	− 1.65	13.43***	2.74	− 6.80	− 1.34
ESP	16.33***	3.48	− 1.47	− 0.25	16.16***	3.44	− 1.93	− 0.33	14.92***	3.20	1.08	0.21	12.85***	2.77	1.35	0.26
FIN	24.53***	4.19	− 7.14	− 0.95	21.82***	3.81	− 5.43	− 0.72	21.81***	3.77	− 5.83	− 0.79	19.63***	3.38	− 11.68	− 1.62
FRA	11.20**	2.47	− 3.79	− 0.72	10.24**	2.26	− 4.63	− 0.88	6.86	1.56	− 6.78	− 1.34	9.65**	1.98	− 7.55	− 1.50
GBR	17.98***	5.57	3.53	1.01	16.41***	5.10	− 1.14	− 0.33	14.72***	4.57	− 2.98	− 0.86	14.62***	4.48	− 6.39**	− 1.97
GRC	33.40***	5.11	8.22	1.14	33.65***	5.12	7.63	1.05	32.01***	4.90	8.21	1.14	33.34***	4.98	2.37	0.33
HKG	29.02***	5.66	− 3.16	− 0.60	27.52***	5.37	− 4.34	− 0.82	25.15***	4.90	− 5.90	− 1.11	24.23***	4.69	− 7.46	− 1.36
ISR	15.20***	2.81	− 4.15	− 0.77	13.61**	2.55	− 6.45	− 1.20	11.56**	2.18	− 8.41	− 1.59	17.44***	2.87	− 3.72	− 0.61
ITA	19.35***	3.11	− 0.53	− 0.06	17.29***	2.81	− 3.03	− 0.40	16.54***	2.68	− 3.57	− 0.47	14.57**	2.40	− 3.69	− 0.49
JPN	14.99***	5.66	0.95	0.33	15.64***	5.68	0.57	0.20	15.25***	5.48	− 0.00	− 0.00	14.09***	5.00	− 2.10	− 0.69
KOR	27.33***	5.55	− 4.12	− 0.83	22.39***	4.69	− 3.89	− 0.78	17.66***	3.88	− 4.12	− 0.83	17.95***	3.88	− 7.78	− 1.55
NLD	15.59***	3.77	0.49	0.11	16.39***	3.80	1.11	0.23	16.30***	3.52	− 2.11	− 0.41	12.94***	3.06	− 4.62	− 0.92
NOR	18.69***	3.53	− 0.26	− 0.05	17.31***	3.27	− 1.62	− 0.29	16.30***	3.06	− 8.85	− 1.30	15.78***	2.93	− 11.02	− 1.63

Table 11 (continued)

Market	Single-trip transaction costs															
	0 Basis points				10 Basis points				25 Basis points				50 Basis points			
	In-sample		Out-of-sample		In-Sample		Out-of-sample		In-sample		Out-of-sample		In-sample		Out-of-sample	
	ΔR	t-Stat	ΔR	t-Stat	ΔR	t-Stat	ΔR	t-Stat	ΔR	t-Stat	ΔR	t-Stat	ΔR	t-Stat	ΔR	t-Stat
PRT	23.04***	5.06	14.13***	2.86	23.65***	5.09	15.10***	2.95	22.35***	4.81	12.84**	2.52	18.88***	4.17	2.96	0.58
SGP	17.67***	3.08	0.69	0.11	16.47***	2.88	− 0.46	− 0.08	15.63***	2.68	− 4.00	− 0.63	17.52***	2.84	− 5.64	− 0.89
SWE	17.77***	3.63	− 3.14	− 0.60	12.47***	2.70	− 2.81	− 0.49	12.23***	2.68	− 4.66	− 0.81	13.19***	2.66	− 5.32	− 0.89
USA	8.29***	3.77	− 5.50**	− 2.11	7.10***	3.26	− 6.25**	− 2.51	8.24***	3.65	− 4.86*	− 1.93	7.53***	3.32	− 5.52**	− 2.22
	Panel B: Emerging markets															
ARG	45.10***	3.53	− 10.61	− 1.10	40.75***	3.21	− 9.92	− 1.05	34.54***	2.76	− 12.30	− 1.31	33.16***	2.65	− 10.74	− 1.15
BGR	34.28***	4.13	2.54	0.41	38.95***	4.46	4.04	0.67	38.80***	4.43	1.07	0.17	37.33***	4.26	− 0.15	− 0.02
BRA	40.84***	3.55	− 4.83	− 0.46	39.98***	3.48	− 5.79	− 0.55	38.49***	3.35	− 6.80	− 0.63	39.47***	3.37	− 8.50	− 0.79
CHL	26.28***	5.16	0.01	0.00	17.05***	3.69	− 5.16	− 1.17	15.38***	3.34	− 7.27*	− 1.65	11.98***	2.63	− 6.45	− 1.49
CHN	19.69**	2.42	3.54	0.39	18.67**	2.29	6.24	0.68	19.63***	2.38	4.84	0.50	16.23**	1.99	− 2.75	− 0.29
COL	26.42***	3.36	− 8.98	− 1.26	25.74***	3.27	− 9.64	− 1.35	24.73***	3.14	− 10.63	0.14	22.24***	2.83	− 9.30	− 1.30
HRV	24.97***	3.78	5.47	0.81	23.58***	3.59	5.65	0.85	27.83***	3.84	4.36	0.62	25.17***	3.50	2.84	0.44
IDN	23.88***	5.18	− 1.86	− 0.38	22.93***	4.96	− 2.90	− 0.58	22.04***	4.78	− 0.73	− 0.15	21.97***	4.64	− 0.62	− 0.12
IND	17.99***	3.58	− 10.08*	− 1.73	20.33***	3.88	− 12.22**	− 2.10	18.67***	3.57	− 12.20**	− 2.25	15.96***	3.11	− 10.64**	− 2.07
MEX	13.50**	2.45	− 17.35***	− 3.20	12.88**	2.33	− 17.15***	− 3.20	13.30**	2.37	− 18.24***	− 3.31	15.09***	2.60	− 18.34***	− 3.19
MYS	25.14***	6.04	− 2.80	− 0.64	24.57***	5.86	− 1.47	− 0.34	24.79***	5.83	− 0.33	− 0.07	21.75***	5.17	− 3.43	− 0.78
PAK	43.72***	6.85	3.93	0.62	36.26***	5.95	− 2.18	− 0.37	31.42***	5.25	− 5.75	− 1.00	32.23***	5.23	− 10.54*	− 1.77
PER	43.65***	6.47	6.48	1.01	37.28***	5.68	3.49	0.55	36.03***	5.48	− 0.39	− 0.06	33.96***	5.16	− 2.48	− 0.39
PHL	28.51***	4.77	− 5.02	− 0.80	25.77***	4.37	− 6.96	− 1.10	24.90***	4.22	− 7.97	− 1.26	25.53***	4.28	− 8.04	− 1.18

Table 11 (continued)

Market	Single-trip transaction costs															
	0 Basis points				10 Basis points				25 Basis points				50 Basis points			
	In-sample		Out-of-sample		In-Sample		Out-of-sample		In-sample		Out-of-sample		In-sample		Out-of-sample	
	ΔR	t-Stat	ΔR	t-Stat	ΔR	t-Stat	ΔR	t-Stat	ΔR	t-Stat	ΔR	t-Stat	ΔR	t-Stat	ΔR	t-Stat
POL	23.51^{***}	3.57	− 1.15	− 0.17	21.75^{***}	3.30	− 3.09	− 0.45	16.81^{***}	2.67	− 6.36	− 0.93	17.09^{***}	2.60	− 10.39	− 1.46
RUS	51.53^{***}	4.23	− 8.20	− 0.73	54.02^{***}	4.33	− 12.63	− − 1.04	52.87^{***}	4.24	− 13.73	− 1.13	50.97^{***}	4.08	− 15.58	− 1.28
SAU	22.96^{***}	3.33	− 6.27	− 0.86	23.51^{***}	3.38	− 5.25	− 0.72	19.61^{***}	2.85	− 8.27	− 1.15	16.61^{**}	2.46	− 8.08	− 1.12
ZAF	23.11^{***}	3.81	− 6.39	− 0.88	15.93^{***}	2.81	− 10.23	− 1.39	14.37^{**}	2.54	− 10.62	− 1.46	15.69^{***}	2.62	− 7.30	− 1.09
	Panel C: Equally weighted portfolios															
Dev	17.12^{***}	10.46	-2.43^{**}	− 2.01	16.01^{***}	9.71	-3.48^{***}	− 2.91	15.48^{***}	9.25	-3.64^{***}	− 3.04	15.19^{***}	8.92	-4.67^{***}	− 3.85
Emg	30.49^{***}	11.20	-4.20^{**}	− 2.25	28.05^{***}	10.53	-6.02^{***}	− 3.22	26.70^{***}	10.00	-6.99^{***}	− 3.71	24.35^{***}	9.21	-7.62^{***}	− 4.03
All	19.44^{***}	12.69	-2.71^{**}	− 2.48	18.15^{***}	11.76	-3.89^{***}	− 3.61	17.58^{***}	11.20	-4.13^{***}	− 3.81	17.07^{***}	10.69	-5.05^{***}	− 4.60

This table reports results for the in-sample and out-of-sample performance of best-performing technical trading rules for single-trip transaction costs of 0, 10, 25, and 50 basis points. Panel A and panel B show results for developed countries and emerging markets, and panel C shows results for equally weighted portfolios of developed (Dev), emerging (Emg), and all market indices (All). ΔR is the difference between annualized returns from technical trading and from a buy-and-hold benchmark (in percentage points), and t-Stat denotes the test statistic obtained from a two-sided t-test. The superscripts ∗∗∗, ∗∗, and ∗ indicate the significance levels of $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively

$$\begin{aligned}&\text{Exit signal for a long position in } t:\\&\left(P_{t-1} > \max\{P_\tau,\ldots,P_{t-2}\}(1-y)\right) \wedge \left(P_t \le \max\{P_\tau,\ldots,P_{t-1}\}(1-y)\right)\\&\text{Exit signal for a short position in } t:\\&\left(P_{t-1} < \min\{P_\tau,\ldots,P_{t-2}\}(1+y)\right) \wedge \left(P_t \ge \min\{P_\tau,\ldots,P_{t-1}\}(1+y)\right)\end{aligned} \tag{13}$$

Moving Averages Let $MA_t^n = n^{-1}\sum_{k=t-n+1}^{t} P_k$ be the simple moving average at time t with a rolling window of length n. A long (short) moving average trading signal is generated when the slow moving average, $MA_t^{n_s}$, crosses the fast moving average, $MA_t^{n_f}$, with $n_s > n_f \ge 1$, from above (below):

$$\begin{aligned}&\text{Long signal in } t: \left(MA_{t-1}^{n_s} \ge MA_{t-1}^{n_f}\right) \wedge \left(MA_t^{n_s} < MA_t^{n_f}\right)\\&\text{Short signal in } t: \left(MA_{t-1}^{n_s} \le MA_{t-1}^{n_f}\right) \wedge \left(MA_t^{n_s} > MA_t^{n_f}\right)\end{aligned} \tag{14}$$

Since Sullivan et al. (1999) also consider moving average rules with $n_f = 1$, the fast moving average in this case becomes $MA_t^1 = P_t$. In this case, we are actually dealing with a single moving average rule, where trading signals are generated by crossovers of the moving average with the asset price.

Support and Resistance In support and resistance trading rules, the asset is bought (sold short) when the close price P_t in period t exceeds (falls below) the high (low) price of the previous n trading days.

$$\begin{aligned}&\text{Long signal in } t:\\&\left(P_{t-1} \le \max\left\{P_{t-n-1},\ldots,P_{t-2}\right\}\right) \wedge \left(P_t > \max\left\{P_{t-n},\ldots,P_{t-1}\right\}\right)\\&\text{Short signal in } t:\\&\left(P_{t-1} \ge \min\left\{P_{t-n-1},\ldots,P_{t-2}\right\}\right) \wedge \left(P_t < \min\left\{P_{t-n},\ldots,P_{t-1}\right\}\right)\end{aligned} \tag{15}$$

We also employ an alternative specification for extrema. As with the alternative specification used for filter rules, a maximum (minimum) is defined as the most recent price that is higher (lower) than the prices of the previous e periods. Consequently, trading signals in period t are triggered according to the following rules.

$$\begin{aligned}&\text{Long signal in } t:\\&\left(P_{t-1} \le P_{\max\limits_{\tilde{t}<t-1}\left\{\tilde{t}\mid P_{\tilde{t}} > \max\left\{P_{\tilde{t}-e-1},\ldots,P_{\tilde{t}-2}\right\}\right\}}\right) \wedge \left(P_t > P_{\max\limits_{\tilde{t}<t}\left\{\tilde{t}\mid P_{\tilde{t}} > \max\left\{P_{\tilde{t}-e},\ldots,P_{\tilde{t}-1}\right\}\right\}}\right)\\&\text{Short signal in } t:\\&\left(P_{t-1} \ge P_{\max\limits_{\tilde{t}<t-1}\left\{\tilde{t}\mid P_{\tilde{t}} < \min\left\{P_{\tilde{t}-e-1},\ldots,P_{\tilde{t}-2}\right\}\right\}}\right) \wedge \left(P_t < P_{\max\limits_{\tilde{t}<t}\left\{\tilde{t}\mid P_{\tilde{t}} < \min\left\{P_{\tilde{t}-e},\ldots,P_{\tilde{t}-1}\right\}\right\}}\right)\end{aligned} \tag{16}$$

Channel breakouts

Trading channels denote price patterns where the minimum and maximum price of the last n trading days differ by no more than a fixed multiplicative value, x. A long (short) channel breakout signal is triggered when the price breaks out of the channel with an upward (downward) movement. This results in the following channel breakout rules.

$$\begin{aligned}
&\text{Long signal in } t: \\
&\left(P_{t-1} \leq \max\left\{P_{t-n-1}, \ldots, P_{t-2}\right\}\right) \\
&\quad \wedge \left(\left(P_t > \max\left\{P_{t-n}, \ldots, P_{t-1}\right\}\right) \wedge \left(\frac{\max\left\{P_{t-n}, \ldots, P_{t-1}\right\}}{\min\left\{P_{t-n}, \ldots, P_{t-1}\right\}} \leq 1 + x\right)\right) \\
&\text{Short signal in } t: \\
&\left(P_{t-1} \geq \min\left\{P_{t-n-1}, \ldots, P_{t-2}\right\}\right) \\
&\quad \wedge \left(\left(P_t < \min\left\{P_{t-n}, \ldots, P_{t-1}\right\}\right) \wedge \left(\frac{\max\left\{P_{t-n}, \ldots, P_{t-1}\right\}}{\min\left\{P_{t-n}, \ldots, P_{t-1}\right\}} \leq 1 + x\right)\right)
\end{aligned} \tag{17}$$

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References

Adekoya, A.F., Asubam, B.A., Nti, I.K.: A systematic review of fundamental and technical analysis of stock market predictions. Artif. Int. Rev. **53**(4), 3007–3057 (2020)

Ahmed, S., Grobys, K., Sapkota, N.: Technical trading rules in the cryptocurrency market. Finan. Res. Lett. **32**, 101396 (2020)

Alexander, S.: Price movements in speculative markets: trends or random walks. Ind. Manag. Rev. **2**(2), 7–26 (1961)

Alexander, S.: Price movements in speculative markets: trends or random walks, number 2. Ind. Manag. Rev. **5**(2), 25–46 (1964)

AlKhazali, O.: Does infrequent trading make a difference on stock market efficiency? Evidence from the gulf cooperation council (GCC) countries. Stud. Econ. Finance **28**(2), 96–110 (2011)

Allen, F., Karjalainen, R.: Using genetic algorithms to find technical trading rules. J. Finan. Econ. **51**(2), 245–271 (1999)
Almazan, A., Brown, K.C., Carlson, M., Chapman, D.A.: Why constrain your mutual fund manager? J. Finan. Econ. **73**(2), 289–321 (2004)
Araújo Lima, E.J., Tabak, B.M.: Tests of the random walk hypothesis for equity markets: evidence from China, Hong Kong and Singapore. Appl. Econ. Lett. **11**(4), 255–258 (2004)
Bailey, D.H., López de Prado, M.: The Sharpe ratio efficient frontier. J. Risk **15**(2), 3–44 (2012)
Bajgrowicz, P., Scaillet, O.: Technical trading revisited: false discoveries, persistence tests, and transaction costs. J. Finan. Econ. **106**(3), 473–491 (2012)
Barras, L., Scaillet, O., Wermers, R.: False discoveries in mutual fund performance: measuring luck in estimated alphas. J. Finance **65**(1), 179–216 (2010)
Batten, J.A., Lucey, B.M., McGroarty, F., Peat, M., Urquhart, A.: Does technical analysis beat the market? – Evidence From high frequency trading in gold and silver, Working Paper (2015)
Bazán-Palomino, W., Svogun, D.: Technical analysis in cryptocurrency markets: do transaction costs and bubbles matter? J. Int. Finan. Mark Institut. Money **79**, 101601 (2022)
Benington, G.A., Jensen, M.C.: Random walks and technical theories: some additional evidence. J. Finance **25**(2), 469–482 (1970)
Benjamini, Y., Hochberg, Y.: Controlling the false discovery rate: a practical and powerful approach to multiple testing. J. Royal Stat. Soci., Series B **57**(1), 289–300 (1995)
Bessembinder, H., Chan, K.: The profitability of technical trading rules in the Asian stock markets. Pacif.-Basin Finance J. **3**(2–3), 257–284 (1995)
Bessembinder, H., Chan, K.: Market efficiency and the returns to technical analysis. Finan. Manag. **27**(2), 5–17 (1998)
Bhuyan, R., Mobarek, A., Mollah, S.: Market efficiency in emerging stock market: evidence from Bangladesh. J. Emerg. Market Finance **7**(1), 17–41 (2008)
Blume, M.E., Fama, E.F.: Filter rules and stock-market trading. J. Bus. **39**(1), 226–241 (1966)
Brock, W., Lakonishok, J., LeBaron, B.: Simple technical trading rules and the stochastic properties of stock returns. J. Finance **47**(5), 1731–1764 (1992)
Camilleri, S.J., Green, C.J.: Stock market predictability: non-synchronous trading or inefficient markets? Evidence from the national stock exchange of India. Stud. Econ. Finance **31**(4), 354–370 (2014)
Campbell, J.Y., Grossman, S.J., Wang, J.: Trading volume and serial correlation in stock returns. Quart. J. Econ. **108**(4), 905–939 (1993)
Chan, L. K. C., & Lakonishok, J.: Institutional trades and intraday stock price behavior. J. Financ. Econ. **33**(2), 173–199 (1993)
Chen, C.-W., Huang, C.-S., Lai, H.-W.: The impact of data snooping on the testing of technical analysis: an empirical study of Asian Stock markets. J. Asian Econ. **20**(5), 580–591 (2009)
Chen, Y.-C., Hsu, Y.-C., Lu, T.-H.: Trend definition or holding strategy: what determines the profitability of candlestick charting? J. Bank. Finance **61**(C), 172–183 (2015)
Cheung, Y.-W., Chinn, M.D.: Currency traders and exchange rate dynamics: a survey of the US market. J. Int. Money Finance **20**(4), 439–471 (2001)
Cohen, G.: Optimizing candlesticks patterns for bitcoin's trading systems. Rev. Quantit. Finance Account. **57**(3), 1155–1167 (2021)
D'Avolio, G.: The market for borrowing stock. J. Finan. Econ. **66**(2–3), 271–306 (2002)
Day, T.E., Wang, P.: Dividends, nonsynchronous prices, and the returns from trading the dow jones industrial average. J. Empir. Finance. **9**(4), 431–454 (2002)
Detzel, A., Liu, H., Strauss, J., Zhou, G., Zhu, Y.: Learning and predictability via technical analysis: evidence from bitcoin and stocks with hard-to-value fundamentals. Finan. Manag. **50**(1), 107–137 (2020)
Duffie, D., Gârleanu, N., Pedersen, L.H.: Securities lending, shorting, and pricing. J. Finance Econ. **66**(2–3), 307–339 (2002)
Etheber, T.: Trading volume effects of moving average heuristics, Working Paper (2014)
Fama, E.F.: The behavior of stock market prices. J. Bus. **38**(1), 34–105 (1965)
Fama, E.F.: Efficient capital markets, A review of theory and empirical work. J. Finance **25**(2), 383–417 (1970)
Farias Nazário, R.T., Kimura, H., Silva, J.L., Sobreiro, V.A.: A literature review of technical analysis on stock markets. Quart. Rev. Econ. Finance **66**(C), 115–126 (2017)
Faugère, C., Smith, D., Wang, Y.: Head and shoulders above the rest? The performance of institutional portfolio managers who use technical analysis, Working Paper (2013)

Friedman, B.: Economic implications of changing share ownership. J. Portf. Manag. **22**(3), 59–70 (1996)
FTSE Group (2016) FTSE annual country classification review, retrieved from http://www.ftse.com/products/downloads/FTSE-Country-Classification-Update_latest.pdf on October 16, 2019
Gatev, E., Goetzmann, W.N., Rouwenhorst, K.G.: Pairs trading: performance of a relative-value arbitrage rule. Rev. Financial Stud. **19**(3), 797–827 (2006)
Gebka, B., Hudson, R., Manahov, V.: Does high frequency trading affect technical analysis and market efficiency? And if so, how? J. Int. Financ. Mark., Institut. Money **28**(1), 131–157 (2014)
Gehrig, T., Menkhoff, L.: Technical analysis in foreign exchange - the workhorse gains further ground, Working Paper (2003)
Gehrig, T., Menkhoff, L.: The use of flow analysis in foreign exchange: exploratory evidence. J. Int. Money Finance **23**(4), 573–594 (2004)
Gompers, P., Metrick, A.: Institutional investors and equity prices. Quart. J. Econ. **116**(1), 229–259 (2001)
Grossman, S.J., Stiglitz, J.E.: On the impossibility of informationally efficient markets. Am. Econ. Rev. **70**(3), 393–408 (1980)
Hackethal, A., Hanspal, T., Lammer, D.M., Rink, K.: The characteristics and portfolio behavior of bitcoin investors - evidence from indirect cryptocurrency investments. Rev. Finance **26**(4), 855–898 (2022)
Hansen, P.R.: A test for superior predictive ability. J. Bus. & Econ. Stat. **23**(4), 365–380 (2005)
Harvey, C.R.: Presidential address: the scientific outlook in financial economics. J. Finance **72**(4), 1399–1440 (2017)
Hoffmann, A.O.I., Shefrin, H.: Technical analysis and individual investors. J. Econ. Behav. Organ. **107**(4), 487–511 (2014)
Hsu, P.-H., Hsu, Y.-C., Kuan, C.-M.: Testing the predictive ability of technical analysis using a new stepwise test without data snooping bias. J. Empir. Finance **17**(3), 471–484 (2010)
Hsu, P.-H., Kuan, C.-M.: Reexamining the profitability of technical analysis with data snooping checks. J. Finan. Econ. **3**(4), 606–628 (2005)
Hsu, P.-H., Taylor, M.P., Wang, Z.: Technical trading: is it still beating the foreign exchange market? J. Int. Econ. **102**(C), 188–208 (2016)
Hudson, R., Urquhart, A.: Technical trading and cryptocurrencies. Ann. Operat. Res. **297**(1), 191–220 (2021)
International monetary fund: world economic outlook april: too slow for too long, Washington (2016)
Irwin, S., Park, C.-H.: What do we know about the profitability of technical analysis? J. Econ. Surv. **21**(4), 786–826 (2007)
Jegadeesh, N., Titman: Returns to buying winners and selling losers: implications for stock market efficiency. J. Finance **48**(1), 65–91 (1993)
Jiang, F., Song, G., Tong, G.: Technical Analysis profitability without data snooping bias: evidence from Chinese stock market. Int. Rev. Finance **19**(1), 191–206 (2019)
Jones, C.M.: A century of stock market liquidity and trading costs, Working Paper (2002)
Jones, C.M., Lamont, O.A.: Short-sale constraints and stock returns. J. Financial Econ. **66**(2–3), 207–239 (2002)
Kaya, O.: High-frequency trading: reaching the limits (2016). retrieved from http://www.dbresearch.com/PROD/RPS_ENPROD/PROD0000000000454703/Research_Briefing%3A_High-frequency_trading.PDF on June 7, 2022
Kish, R.J., Kwon, K.-Y.: A comparative study of technical trading strategies and return predictability: an extension of Brock, Lakonishok, and LeBaron (1992) using NYSE and NASDAQ indices. Quart. Rev. Econ. Finance **42**(3), 611–631 (2002)
Lease, R.C., Lewellen, W.G., Schlarbaum, G.G.: The individual investor: attributes and attitudes. J. Finance **29**(2), 413–433 (1974)
Lease, R. C., Lewellen, W. G., & Schlarbaum, G. G.: Portfolio design and portfolio performance: the individual investor. J. Econ. Bus. **32**(3), 185–197 (1980)
LeBaron, B.: The stability of moving average technical trading rules on the Dow Jones index. Derivatives Use Trad. Regul. **5**(4), 324–338 (2000)
Lesmond, D.A.: Liquidity of emerging markets. J. Finan. Econ. **77**(2), 411–452 (2005)
Levy, R.A.: Random walks: reality or myth. Finan. Anal. J. **23**(6), 69–77 (1967)
Levy, R.A.: Relative strength as a criterion for investment selection. J. Finance **22**(4), 595–610 (1967)
Levy, R.A.: Random walks: reality or myth - reply. Finan. Anal. J. **24**(1), 129–132 (1968)
Lo, A.W.: The adaptive markets hypothesis. J. Portf. Manag. **30**(5), 15–29 (2004)

Lo, A.W., MacKinlay, A.: When are contrarian profits due to stock market overreaction? Rev. Financial Stud. **3**(2), 175–205 (1990)
Lo, A.W., MacKinlay, A.: Data snooping biases in tests of financial asset pricing models. Rev. Finan. Stud. **3**(3), 431–467 (1990)
Lo, A.W., Wang, J.: Trading volume: definitions, data analysis, and implications of portfolio theory. Rev. Finan. Stud. **13**(2), 257–300 (2000)
Malkiel, B.G.: A random walk down wall street, revised edition, United States, New York (1999)
Marshall, B.R., Nguyen, N., Visaltanachoti, N.: Time-series momentum versus technical analysis. Quantit. Finance **17**(3), 405–421 (2017)
Menkhoff, L.: Examining the use of technical currency analysis. Int. J. Finance Eco. **2**(4), 307–318 (1997)
Menkhoff, L.: The use of technical analysis by fund managers: international evidence. J. Bank. Finance **17**(3), 547–564 (2010)
Merton, R.: On the current state of the stock market rationality hypothesis. In: Dornbusch, R., Fischer, S., Bossons, J. (eds.) Macroeconomics and finance: essays in honor of Franco Modigliani. United States, Cambridge (1987)
Moskowitz, T.J., Ooi, Y.H., Pedersen, L.H.: Time series momentum. J. Finan. Econ. **104**(2), 228–250 (2012)
Nagel, S.: Short sales, institutional investors and the cross-section of stock returns. J. Finan. Econ. **78**(2), 277–309 (2005)
Neely, C.J.: Risk-adjusted, ex ante, optimal technical trading rules in equity markets. Int. Rev. Econ. Finance **12**(1), 69–87 (2003)
Neely, C.J., Dittmar, R., Weller, P.A.: Is technical analysis in the foreign exchange market profitable? A genetic programming approach. J. Finan. Quantit. Anal. **32**(4), 405–426 (1997)
Neely, C. J., Rapach, D. E., Tu, J., Zhou, G.: Out-of-sample equity premium prediction: economic fundamentals vs. moving-average Rules, Federal Reserve Bank of St. Louis, Working Paper (2010)
Neely, C.J., Weller, P.A.: Technical analysis in the foreign exchange market, federal reserve bank of St. Louis, Working Paper (2011)
Neely, C.J., Weller, P.A., Ulrich, M.: The adaptive markets hypothesis: evidence from the foreign exchange market. J. Finan. Quantit. Anal. **44**(2), 467–488 (2009)
Neftci, S.N.: Naive trading rules in financial markets and wiener-kolmogorov prediction theory: a study of "technical analysis''. J. Bus. **64**(4), 549–571 (1991)
Olsen, D.: Have trading rule profits in the currency markets declined over time? J. Bank. Finance **28**(1), 85–105 (2004)
Politis, D.N., Romano, J.P.: The stationary bootstrap. J. Am. Stat. Associat. **89**(428), 1303–1313 (1994)
Poshakwale, S.: The random walk hypothesis in the emerging Indian stock market. J. Bus. Finance Account. **29**(9 & 10), 1275–1299 (2002)
Pring, M.J.: Technical analysis explained, 5th edn. United States, New York (2014)
Ready, M.J.: Profits from technical trading rules. Finan. Manag. **31**(3), 43–61 (2002)
Romano, J.P., Wolf, M.: Stepwise multiple testing as formalized data snooping. Econometrica **73**(4), 1237–1282 (2005)
Rouwenhorst, K.G.: International momentum strategies. J. Finance **53**(1), 267–284 (1998)
Scholes, M., Williams, J.: Estimating betas from nonsynchronous data. J. Finan. Econ. **5**(3), 309–327 (1977)
Sharma, A., Thaker, K.B.: Market efficiency in developed and emerging markets. Afro-Asian J. Finance Account. **5**(4), 311–333 (2015)
Sharpe, W.F.: Mutual fund performance. J. Bus. **39**(1), 119–138 (1966)
Sharpe, W.F.: The Sharpe ratio. J. Portf. Manag. **21**(1), 49–58 (1994)
Stoll, H.R., Whaley, R.E.: Transaction costs and the small firm effect. J. Finan. Econ. **12**(1), 57–79 (1983)
Subrahmanyam, A.: Equity market momentum: a synthesis of the literature and suggestions for future work. Pacific-Basin Finance J. **51**, 291–296 (2018)
Sullivan, R., Timmermann, A., White, H.: Data-snooping, technical trading rule performance, and the bootstrap. J. Finance **54**(5), 1647–1691 (1999)
Sweeney, R.J.: Beating the foreign exchange market. J. Finance **41**(1), 163–182 (1986)
Timmermann, A.: Elusive return predictability. Int. J. Forecast. **24**(1), 1–18 (2008)

Timmermann, A., Granger, C.W.J.: Efficient market theory and forecasting. Int. J. Forecast. **20**(1), 15–27 (2004)
United Nations: world economic survey, 1974 - Part One. Mid-term review and appraisal of progress in the implementation of the international development strategy, New York, United States (1975)
White, H.: A reality check for data snooping. Econometrica **68**(5), 1097–1126 (2000)
Wiest, T.: Momentum: what do we know 30 years after Jegadeesh and Titman's seminal paper? Finan. Mark. Portf. Manag. **37**(1), 95–114 (2023)
Wilder, J.W.: New concepts in technical trading systems. Greensboro, United States (1978)

Kevin Rink is an external researcher at the Faculty of Economics and Business at Goethe University Frankfurt, where he also obtained his doctoral degree in finance. Prior to that, he received a master's degree in business administration from the University of Mannheim and a master's degree in quantitative finance from Goethe University Frankfurt. His research interests include financial markets, behavioral finance, and household finance with a special focus on technical trading heuristics and investor behavior in equity and cryptocurrency markets.