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## Working Paper

The trend is not your friend! Why empirical timing success is determined by the underlying's price characteristics and market efficiency is irrelevant

CPQF Working Paper Series, No. 29

## Provided in Cooperation with:

Frankfurt School of Finance and Management

*Suggested Citation:* Scholz, Peter; Walther, Ursula (2011) : The trend is not your friend! Why empirical timing success is determined by the underlying's price characteristics and market efficiency is irrelevant, CPQF Working Paper Series, No. 29, Frankfurt School of Finance & Management, Centre for Practical Quantitative Finance (CPQF), Frankfurt a. M.

This Version is available at:

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## CPQF Working Paper Series

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No. 29

**The Trend is not Your Friend!**  
**Why Empirical Timing Success is Determined by the Underlying's Price  
Characteristics and Market Efficiency is Irrelevant**

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July 2011

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Publisher:

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# The Trend is not Your Friend!

## Why Empirical Timing Success is Determined by the Underlying's Price Characteristics and Market Efficiency is Irrelevant

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Working Paper, Version: 22 June 2011

### Abstract

The often reported empirical success of trend-following technical timing strategies remains to be puzzling. In previous academic research, many authors admit some prediction power but struggle to substantiate their findings by referring vaguely to insufficient market efficiency or unknown hidden patterns in asset price processes. We claim that empirical timing success is possible even in perfectly efficient markets but does not indicate prediction power. We prove this by systematically tracing back timing success to the statistical characteristics of the underlying asset price time series, which is modeled by standard stochastic processes. Five major impact factors are studied: return autocorrelation, trend, volatility and its clustering as well as the degree of market efficiency. We use trading rules based on different intervals of the simple moving average (SMA) as an example. These strategies are applied to simulated asset price data to allow for systematic parameter variations. Subsequently, we test the same strategies on real market data using non-parametric historical simulations and compare the results. Evaluation is done by an extensive selection of statistical-, return-, risk-, and performance figures calculated from the simulated return distributions.

**Keywords:** Bootstrapping, Market Efficiency, Market Timing, Parameterized Simulation, Performance Analysis, Return Distribution, Technical Analysis, Technical Trading.

**JEL Classification:** G11, G14

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*“It is said that the military is usually well prepared to fight the previous war. A number of investors now engaging in active market timing appear to be preparing for the previous market. Unfortunately for the military, the next war may differ from the last one. And unfortunately for investors, the next market may also differ from the last one.”*

William F. Sharpe (1975)

## I Introduction

“Timing is money” was one of the maxims of André Kostolany (1906-1999), the famous grand seigneur of speculators. Indeed, from a retrospective point of view, observed market swings seem to offer great trading opportunities, seducing investors with the traditional market’s adage “buy low and sell high”. But is it possible to anticipate, or even more, benefit from these price cycles?

Academics traditionally doubt sustainable benefits from active investment strategies due to their immediate contradiction with the efficient market hypothesis.<sup>1</sup> Nevertheless, a meanwhile substantial amount of academic studies have used technical trading rules as an instrument to test for market efficiency (e.g. Brock, Lakonishok & LeBaron 1992, Conrad & Kaul 1998, Sullivan, Timmermann & White 1999, Fifield, Power & Sinclair 2005, Hon 2006). Surprisingly, the studies widely confirm at least some forecasting power of past prices. The reasons for those findings are not yet well understood, however. Authors tentatively argue with a lack of market efficiency and hidden patterns in asset price time series, which cannot be reproduced by simulations.

In this paper, we show that technical timing may generate alleged “outperformance” by simply exploiting price process characteristics, which are measurable by standard time series models. Hence, empirical timing success does not indicate market inefficiency. We consider four parameters of standard time series models for asset price processes: the trend (or drift)  $\mu$  and the volatility of returns  $\sigma$  of a generalized Brownian motion, the serial autocorrelation parameter  $\varphi$  of an AR(1) process, and finally the volatility autocorrelation  $\beta$  of a GARCH(1,1) process. Our findings on the systematic link between price process parameters and timing success allow us to either substantiate or refuse several hypotheses formulated in the literature. First, we find a negative impact of the drift on timing strategies (similar to Hilpold & Kaiser 2005). Second, we confute that trend following timing approaches could not exploit cycles caused by autocorrelated returns as claimed by Tucker (1992). Third, we clarify the contradicting statements regarding the impact of volatility: whereas for example Brock et al. (1992) suggest no or just a minimal impact, Hilpold & Kaiser (2005) assume a positive and Dunis & Miao (2004) a negative one.

<sup>1</sup>Following Sharpe (1975), the asset management literature splits the potential outperformance sources of investment strategies into the selection process (e.g. stock picking) and adjustments of the portfolio’s exposure to forecasted bull and bear periods, which is also known as  $\beta$ -management or *market timing*.

According to our findings, the influence from volatility is comparatively weak. Finally, we are able to elucidate the often reported empirical finding (as discussed in more detail in Section II) that developed markets are harder to time than emerging ones due to a lower degree of market efficiency. Instead, we can trace back the empirical results to the statistical parameters of the respective data sample.

Our study uses simulation approaches. Therefore, we are able to analyze the whole return distribution of a strategy.<sup>2</sup> We both use parametric generated data, which allow systematic parameter variations, and historical bootstraps, which capture real market characteristics. The empirical dataset comprises ten years of daily prices (from 2000 to 2009) for 35 different leading stock market indices from all over the world. The return distribution of a buy-and-hold-strategy is then compared to the one resulting from applying a timing strategy. This comparison reveals the full “return shaping effect” of a strategy and its dependence on the properties of the underlying asset price process. In order to evaluate success, an extensive set of statistical-, return-, risk-, and performance figures is used.

The evaluation of the full return distributions allows us to assess the risk implications of timing strategies in great detail. It has been suspected that investors use timing strategies especially in bear markets as a kind of portfolio insurance to avoid substantial losses. Institutional investors particularly apply so-called *trading systems* as a prominent active management strategy in order to “shape” the return distribution of the benchmark, i.e. to get a better match with the client’s preferences. Our results confirm a certain level of portfolio protection only under specific circumstances. However, this comes at the price of a significant increase in tail risk due to an increased probability of “bleeding out” from repeated losses.

Our study is exemplary in that it uses the popular simple moving average (SMA) trading rule only. As a result, it shows that timing results are independent from the degree of market efficiency. Moreover, we reject the idea that trading rules based on technical analysis have any prediction power at all. They rather turn out to systematically react on the statistical properties of the underlying asset price process. If these properties are beneficial, then a technical trading rule will generate excess returns no matter how efficient the market is. But the strategy can by no means predict such a favorable market environment.

After a short literature review (Section II) we explain our methodology and data (Section III). Section IV presents our simulation results and summarizes the risk and performance implications. Section V concludes.

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<sup>2</sup>Similar methods were used by Annaert, van Osselaer & Verstraete (2009) to assess protection strategies.

## II Literature Review

An investor who enters and leaves a volatile market with perfect forecasting ability would obviously earn much higher returns and bear lower risks than the market average (Ebertz, Kosiolek & von Rhein 2002). Due to the apparent contradiction to the efficient market hypothesis, researchers are reluctant to trust sustainable benefits from active management strategies such as timing. Indeed, most empirical studies do not find market timing abilities if the task is to annually forecast the prospects of the risky asset class and to invest accordingly. Presumably, the first study of this kind was published by Treynor & Mazuy (1966), who found no evidence for mutual fund managers' ability to outguess their benchmark. Another important study by Sharpe (1975) concludes that "the potential gains from market timing are likely to be modest at best", and that "only a manager with truly superior predictive ability should even attempt to time the market." These findings were discussed in several later studies. For instance, Ehm, Seubert & Weber (2009) do not see any empirical evidence for timing skills and seriously doubt any timing success, whereas Bauer & Dahlquist (2001) report heterogeneous results in different empirical studies. A possible explanation for the weak empirical evidence is the insufficient length of the observed time series to statistically prove or reject success. This is a common problem to studies on forecasting ability. Like Beebower & Varikooty (1991) point out, only very strong timing abilities could obtain statistically significant results: even an exorbitant 100 bps outperformance per month is statistically only detectable after at least four years. The confirmation of realistic skills, by contrast, typically requires a manager's track record longer than an individual's lifetime.<sup>3</sup>

A different approach to market timing is the application of a digital series of buy and sell signals, so-called *timing signals*. Trading rules based on technical indicators are a popular method to generate such entry and exit points for market investments. The performance potential of timing signals has been under study by practitioners as well as academics for more than 50 years.<sup>4</sup> Among academics, the prediction power of technical trading rules has often been used as a test of the weak-form informational efficiency of markets (Hon 2006). Park & Irwin (2007) provide a review of 137 studies from 1960 to 2004, categorized into early (1960-1987) and modern studies (since 1988). The earliest ones considered are Donchian (1960) and Alexander (1961),

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<sup>3</sup>Bodie, Kane & Marcus (2009) present an example, where all potential statistical problems are intentionally biased in favour of the portfolio manager. It would need 32 years to verify skill against luck on a 5% significance level, however.

<sup>4</sup>The timing literature splits into different lines referring to general "market timing", in which the source from prediction is irrelevant; or to "technical trading", which is purely based on technical analysis. Interestingly, no one has brought these two strands together, although technical trading rules are nothing more than coded market timing.

which analyze several different technical trading systems, first and foremost filter rules,<sup>5</sup> moving averages and relative strength. According to Park & Irwin (2007), the overall results in the early studies indicate that trading systems on stock markets are largely not profitable, whereas significant net profits seem to be attainable in foreign exchange as well as futures markets. A prominent example among those studies is Fama & Blume (1966), who compared filter rules to a naïve buy-and-hold strategy and found lower returns even before transaction costs.<sup>6</sup> However, early studies are subject to a couple of limitations: they generally only consider a small selection of trading systems, statistical tests of significance are not conducted or insufficient, the riskiness of returns is mostly ignored, and profits are often due to data snooping biases.

The work of Lukac, Brorsen & Irwin (1988) is considered the first modern study, which is more comprehensive and overcomes many of the previous deficiencies. The modern studies still vary in their handling of transaction costs, risk consideration, parameter optimization, data snooping biases and out-of-sample as well as statistical tests. Presumably the most influential study is the work of Brock et al. (1992), who applied simulation methods to test statistical significance of trading rule returns. They compare the profits generated by timing strategies on Dow Jones Industrial Average (DJIA) prices from 1897 to 1986 with those generated on simulated price series: a random walk, autoregressive processes (AR(1)) and generalized autoregressive conditional heteroscedasticity models (GARCH-M, EGARCH). As trading rules they choose the moving average-oscillator and trading range break-outs, which are considered popular and hence representative. The study finds significant risk-adjusted excess returns in the real world data (measured against the simulated series). The authors thus conclude: “it is quite possible that technical rules pick up some of the hidden patterns [of the returns-generating process of stocks]”, which are missed in simulated price series.

The provocative results in Brock et al. (1992) inspired a vast amount of follow-up studies. Bessembinder & Chan (1998) reran the analysis on a dividend-adjusted DJIA price series applying non-synchronous trading with a one-day lag. Even though the trading profits became slightly smaller, still some technical prediction power was left. Other studies were conducted using different market data. For instance, Hudson, Dempsey & Keasey (1996) used the Brock et al. methodology on UK stock prices from 1935 to 1994. They confirm the results for the UK data but draw a different conclusion. According to them, predictive power of technical trading reveals if (a) the price series is long enough and (b) in absence of transaction costs. In contrast to Brock et al., they interpret their results as in-line with the weak form efficiency of stock mar-

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<sup>5</sup>In this context, the term *filter* denotes a special trading rule, where a buy (sell) signal is generated, if the current closing price is above (below) a certain price level. *Filter* also describes a method to reduce whiplash signals.

<sup>6</sup>Sweeney (1988, 1990) re-examined some of the Fama & Blume (1966) findings and, by contrast, detected risk-adjusted excess returns even if transactions costs were included.

kets, since transaction costs would eliminate the trading profits. In order to compare a broader range of markets, Fifield et al. (2005) analyzed eleven European stock markets<sup>7</sup> from 1991 to 2000. They found that the European stock markets exhibit different stock price characteristics and concluded that developed countries seem to be rather efficient, whereas emerging markets did show some predictability in their returns. Similar findings were described in Bessembinder & Chan (1995), who compared Asian emerging markets (Malaysia, Thailand, Taiwan) with developed ones (Hong Kong, Japan). Numerous other studies, investigating even very small (and maybe inferior) markets such as Jamaica (Hunter 1998), Chile (Parisi & Vasquez 2000), Jordan (Atmeh & Dobbs 2006), or Iran (Razmi, Joulai & Emami 2008), to name only a few, confirmed this hypothesis. The common explanation can be found in Papathanasiou & Samitas (2010), who investigated Cypriot stock market data: emerging markets are less efficient due to lower levels of liquidity, poor analyst coverage and missing derivative products.

Other studies tackled the issue of potential data snooping bias. Sullivan et al. (1999), for example, applied White's (2000) especially developed bootstrap reality check methodology to test a vast amount of different trading systems on a very long time series.<sup>8</sup> They found that the results of Brock et al. (1992) are robust to data snooping biases. However, the out-of-sample tests applied to the time period of 1987 to 1996 were rather disappointing. Even the most successful trading systems did not continue to deliver superior results. Again, the authors refer to market efficiency and interpret their results as a sign for improved informational efficiency of U.S. stock markets in the out-of-sample period.

Summarizing the so-called modern studies, Park & Irwin (2007) found a vast majority supporting technical trading profits: from a total of 95 studies, 56 confirmed the profitability of technical trading, whereas just 20 rejected it. Within stock markets only, 26 out of 48 studies claim profits from technical trading. However, some puzzles remain: successful trading systems fail in out-of-sample tests<sup>9</sup> and contrarian as well as trend-following systems seem to work simultaneously, although they are opposed strategies. The studies are generally remarkably weak in explaining the sources of the prediction power and thus the apparent economic benefit. The effect is largely assigned to either time series patterns,<sup>10</sup> caused for example by business cycles, money supply growth, or systematic behavioral effects like herding (Conrad & Kaul 1998), or the inefficiency of markets (e.g. Kwon & Kish 2002), especially in case of emerging markets (Marshall, Cahan & Cahan 2010).

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<sup>7</sup>Using their classification: major developed markets (France, Germany, and the UK), small developed markets (Finland, Italy, Ireland, and Spain), and emerging markets (Greece, Hungary, Portugal, and Turkey).

<sup>8</sup>They tested about 8,000 different rules and implementations on a DJIA series from 1897 to 1996.

<sup>9</sup>The typical explanation is increased market efficiency. Ready (2002) suggests that opportunities were "traded away" by professionals.

<sup>10</sup>Ready (2002) notes that those patterns need not necessarily be persistent in the future.

Another line of literature is less interested in market efficiency but focuses on specific timing characteristics and risk topics. An issue often discussed is the underinvestment on the most important days. As Taleb (2007) or Estrada (2008) point out, large market movements on single days are crucial for the long term stock market performance. The overall S&P 500 return during the last 50 years shrinks by around 50% if one excludes the ten strongest one-day returns. Since these so-called “black swans” seem impossible to predict, every market timing strategy suffers from the risk of missing those outliers. Additionally, their distribution differs between positive and negative returns (Shilling 1992). If an investor had missed the 50 strongest months of the Dow Jones Industrial Average index from 1946-1991, his annual profit would fall from 11.2% to 4% for a buy-and-hold strategy. If he had avoided the 50 most bearish months, the annual return would rise to 19%,<sup>11</sup> an impressive reward from timing. Avoiding losses naturally also has a base effect: as a decrease of 50% needs a profit of 100% for compensation, the avoidance of bear markets leaves more money to profit from a rebound. Summarizing these effects, Faber (2007) refers to timing as “a risk-reducing technique rather than a return-enhancing one,” because it helps to avoid large drawdowns, reduces volatility and improves risk-adjusted returns due to the avoidance of bear markets. The price for this were an underperformance in “roaring bull markets” only. As is typical in practice oriented literature, the study argues with trade statistics to substantiate its findings. Faber’s trading rule, which is similar to the SMA(200), produces few large gain- or loss trades rather than of more frequent smaller ones. Compared to a loss trade, the duration of an average win trade is found to be six times longer and its size seven times larger. Additionally, the hit ratio<sup>12</sup> was uncharacteristically high at 54% and the trading frequency moderate.<sup>13</sup> Faber’s findings are based on a backtest of 33 years, in which positive serial correlation (also known as the market’s momentum) serves as the main explanation for the timing benefits; subsequent studies refused these findings. Marmi, Pacati, Renò & Risso (2009), for example, apply the same trading rule on price series generated by historical simulation. They find that the outperformance of Faber’s trading system lies within the statistical variability of historical returns and does not prove a dominant investment strategy.

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<sup>11</sup>This asymmetry is a clear indication that timing strategies alter not only the return but also the risk with respect to their benchmark.

<sup>12</sup>The hit ratio denotes the percentage of win trades compared to the total trades during the sample period.

<sup>13</sup>Overall, Faber’s timing strategy only generated 3-4 round trip trades per year on average and is invested around 70% of the time.

### III Data & Methodology

We examine how simple moving average trading rules alter the return distribution of a given asset.<sup>14</sup> In contrast to existing timing literature, this allows to examine the risk-return profile in great detail. We therefore simulate asset prices by standard time series models and a non-parametric historical bootstrap method based on real world data. The trading rules are then applied to those random price series. Unlike a standard backtest, which only analyses the single historically observed price path, our approach delivers the entire return distribution of terminal results. From these, we deduce a wide range of return-, risk-, as well as performance figures and additionally evaluate trade statistics. This provides a comprehensive picture to assess the success and risk characteristics of a strategy. Throughout this work, the buy-and-hold approach serves as a benchmark.

Moreover, the parametric simulations allow us to analyze the impact from systematic variations of the asset price characteristics on the timing performance. In doing so, we focus on drift ( $\mu$ ), volatility ( $\sigma$ ), autocorrelation ( $\varphi$ ) and volatility clustering ( $\beta$ ). Those findings enable us to formulate predictions regarding the performance of a timing strategy on a given real world data set. Our forecasts are verified against the results from the historical bootstraps.

#### III.1 Simulation Approaches

##### III.1.1 Parametric Simulation

As the most basic model for stock returns and a point of reference we use a discretized random walk with drift as given by

$$r_t = \ln(S_t/S_{t-1}) = \mu \cdot \Delta_t + \sigma \cdot \sqrt{\Delta_t} \cdot \varepsilon_t \quad (1)$$

where  $S_t$  denotes the stock price at time  $t$ ,  $\Delta_t = 1/250$  a time interval of one day, and  $\varepsilon_t$  a standard-normal random variable (Glasserman 2003). This first model allows to analyze the impact of the drift (or trend)  $\mu$  and the standard deviation (or volatility)  $\sigma$  on timing success.

A random walk model creates normally distributed returns. Stock market returns, however, typically exhibit some well known stylized facts such as fat tails, time varying volatility or clustering of extreme returns (McNeil, Frey & Embrechts 2005). This is confirmed by the descriptive statistics of our data sample, where all 35 markets show such non-normality. As a first step to incorporate the fat tail effect, we allow for autocorrelated returns. Moreover, autocorrelation plays a special role with respect to timing as it is suspected to generate some kind of cyclic behavior of asset returns. This should be exploitable by timing strategies. Statistical

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<sup>14</sup>We refer to any shifts between the underlying's and the strategy's return distribution as *return shaping*.

tests indicate that short time lags have the strongest impact on future returns (Cerqueira 2006). Therefore, we use a first-order autoregressive process AR(1) as given by  $r_t = \varphi \cdot r_{t-1} + \varepsilon_t$ , such that the full model with drift results in

$$r_t = \mu \cdot \Delta_t + \varphi \cdot r_{t-1} + \sigma \cdot \sqrt{\Delta_t} \cdot \varepsilon_t. \quad (2)$$

This second model allows us to study the impact of the autocorrelation parameter  $\varphi$  on the timing distribution.

Many empirical time series exhibit rather limited evidence for significant autocorrelated returns (McNeil et al. (2005)). Instead, there is often an indication for autocorrelated squares of returns, i.e. autocorrelation in return variances. This phenomenon is also called heteroscedasticity or volatility clustering. A standard approach to simulate price paths with volatility clustering is by a GARCH(1,1) model according to Bollerslev (1986), where the volatility of the process is described as  $\sigma_t^2 = \omega + \alpha \cdot r_{t-1}^2 + \beta \cdot \sigma_{t-1}^2$ , with the parameters  $\alpha$  (return autocorrelation),  $\beta$  (volatility autocorrelation) and  $\omega$  (mean level volatility). The full model thus evolves as

$$r_t = \mu \cdot \Delta_t + \sigma_t \cdot \sqrt{\Delta_t} \cdot \varepsilon_t \quad (3)$$

$$\sigma_t^2 = \omega + \alpha \cdot r_{t-1}^2 + \beta \cdot \sigma_{t-1}^2. \quad (4)$$

Timing strategies applied to underlyings, which are simulated by this model provide insight whether the level of the volatility clustering parameter  $\beta$  affects the timing results or not.

For every parametric simulation, 10,000 paths are generated which produce stable results.<sup>15</sup> All paths comprise 2,500 data points, which corresponds to 10 years with 250 trading days. Additionally, a forerun of prices ensures the availability of an SMA value for the first day. The initial underlying asset price is always set to 100 €.

### III.1.2 Non-Parametric Historical Bootstrap Technique

To verify our findings from the parametric simulations, we apply a historical simulation based on real market data as introduced by Tompkins & D'Ecclesia (2006). This non-parametric bootstrap technique has been designed to reproduce the information given in the data with as little distortion as possible.<sup>16</sup> No assumptions about the underlying distribution or parameter estimates are necessary. The method is computationally very efficient. In our case,  $n = 1,000$  paths were enough to get stable results.

Following this approach, we calculate daily log-returns  $r_d$  from the original price series. A conditional volatility model is then adopted to capture the inter-temporal volatility dynamics. We again use a standard GARCH(1,1) model as described above. The resulting state dependent

<sup>15</sup>A simulation with 100,000 paths was also run to verify that the results are stable enough.

<sup>16</sup>A similar approach can be found in Annaert et al. (2009), who use a block bootstrapping technique.

volatilities  $\widehat{\sigma}_d$  are used to standardize the daily returns. The results are the daily unconditional devolitized disturbances

$$udd_d = \frac{r_d - \bar{r}_d}{\widehat{\sigma}_d} \quad (5)$$

where  $\bar{r}_d$  denotes the mean of the raw returns. These standardized returns are assumed to be independent, allowing a random remixing to generate new paths. Accordingly, a new path is created by reshuffling the  $udd_d$  variables such that each return is taken exactly once (sampling without replacement) and revolatizing it with the previously estimated GARCH(1,1) volatility.<sup>17</sup> The prices of the new paths are thus generated as

$$S_t = S_{t-1} \cdot e^{\bar{r}_d + udd_d \cdot \widehat{\sigma}_d}. \quad (6)$$

This simulation technique delivers alternative price paths with almost the same statistical properties as the original one. However, due to the resampling process, the serial autocorrelation structure is destroyed and hence cannot be tested. A block bootstrap approach could solve this problem, but its application requires a quite long time series.<sup>18</sup> Especially for emerging markets, it is typically not available.

### III.2 Database and Descriptive Statistics

In the study, we use 35 leading equity indices from all over the world [cf. table (1)]. The sample covers all major developed markets as well as the BRIC and the N-11 emerging markets<sup>19</sup> and therefore represents a good geographical mix. The database contains daily closing prices from 1 January 2000 to 31 December 2009, taken from Thomson Reuters.

Table (2) presents the descriptive statistics of the 35 indices including mean return  $\mu$ , standard deviation  $\sigma$ , skewness and kurtosis as well as the first-lag autocorrelation parameter  $\varphi$ , the GARCH parameters  $\alpha$ ,  $\beta$ , and  $\omega$  and a Jarque-Bera test on normality. These figures realistically indicate the parameter range of real world data. We therefore use the extremes as bounds in our parameterized simulations.<sup>20</sup>

<sup>17</sup>One also could revolatize by a newly generated series of GARCH(1,1)-volatilities using the estimated parameters  $\gamma$ ,  $\alpha$  and  $\beta$ . This would increase variation but at the cost of losing independence from parameters.

<sup>18</sup>Moreover, as Cogneau & Zakamouline (2011) state, the simulation results may be biased if certain block bootstrap techniques are applied.

<sup>19</sup>The terms *BRIC* and *N-11* have been introduced by Goldman Sachs Chief Economist Jim O'Neill. BRIC denotes the **B**razilian, **R**ussian, **I**ndian and **C**hinese markets; N-11 describes the so-called Next Eleven emerging markets, i.e. Bangladesh, Egypt, Indonesia, Iran, Mexico, Nigeria, Pakistan, the Philippines, South Korea, Turkey, and Vietnam. Those countries are seen to be most likely to follow the BRIC markets in their development. In our study, we had to exclude Bangladesh, Egypt, Iran, Nigeria, and Vietnam due to their short time series.

<sup>20</sup>It should be noted that the empirical levels of the parameters may not be stable over time.

The results of the descriptive analysis are completely in line with expectations. None of the equity markets shows a normal return distribution. Approximately two-thirds of the indices' distributions are left-skewed, the lowest skewness is -0.9722 (Saudi-Arabia), the highest 0.5627 (the Philippines). All return distributions exhibit excess kurtosis (from 4.80 in Poland to 19.16 in the Philippines). The average daily returns deviate between -0.0004638 (Greece) and 0.0009027 (Peru) with a mean of 0.0002078. The average daily standard deviations range from 0.0103 (Australia) to 0.249 (Turkey) with a mean of 0.0164. The autocorrelation levels in the markets are mostly small or even negative, fluctuating between -0.2064 (Peru) and 0.1027 (U.S.A.) with an average mean of 0.0240. By tendency, the emerging markets exhibit slightly positive autocorrelations levels, whereas the developed markets largely show negative ones. The GARCH volatility autocorrelation parameter  $\beta$  varies from 0.7350 (Peru) to 0.9424 (Poland) with an average of 0.8739.

### III.3 The Simple Moving Average Trading Rule

A technical trading rule is an algorithm that converts information from past prices, and partly other related technical data like market- or order book statistics, into a digital series of buy and sell signals. According to the signals, the exposure is shifted between the risky benchmark, for example a stock market index, and the risk free alternative, i.e. cash. The price path, which is finally generated by the trading rule is referred to as *equity curve* or *active portfolio*.

Simple moving averages are a rather old trading rule (e.g. Gartley 1930) and a very popular example in the academic literature. The basic idea behind this timing system is to follow established trends, which may be caused e.g. by herding effects (Heidorn & Siragusano 2004) or over- and underreaction (Jasic & Wood 2004). Following, an SMA strategy may also prevent investors from giving into the disposition effect (Nöth 2005).

The SMA is the unweighted mean of the previous  $d$  asset prices  $p_i$  and calculated such that the present day  $t + 1$  does not enter the calculation:

$$SMA(d)_{t+1} = \frac{1}{d} \cdot \sum_{i=t-d}^t p_i. \quad (7)$$

If  $p_t \geq SMA(d)_t$ , then the system generates a buying signal, i.e. exposure is built up. If  $p_t < SMA(d)_t$ , then a selling signal is triggered and the corresponding position is closed.

The practical implementation of an SMA trading rule needs additional specifications, however.<sup>21</sup> We implement the trading rule with an asset management but not a day trading context

<sup>21</sup>It is worth noting that most academic studies give little or no attention to the exact implementation issues, even though the implementation does affect the strategy's return profile. In subsequent research, we analyze the impact of risk- and money management on timing results.

in mind. Thus, we do not allow short positions and care for a moderate turnover to confine transaction costs, even if we do not consider them explicitly in our study. Furthermore, it is important to note that the timing signals derive from the technical trading rule only. No additional instruments to limit the exposure such as stop-loss levels are applied. Our assumptions are also meant to ensure that the pure influence from timing is analyzed but risk management, transaction costs or interest rate sensitivity are excluded. As SMA intervals, we apply the 5, 10, 20, 38, 50, 100, and 200 day average. This represents a range of different sensitivities and corresponds to systems as applied in practice.<sup>22</sup> If a signal is triggered, one share of the underlying benchmark is bought or sold.<sup>23</sup> In case of a low cash account, buying a full share may require the investor to take credit, which is possible as long as the investor's net position still has a positive value. We neither consider interest on the risk free cash account or dividend payments on stocks nor allow for credit rates. Nevertheless, the leverage may cause losses beyond the initial investment and hence lead to insolvency of the investor. If a strategy on a given price path loses the total initial investment, then the strategy ceases, the terminal value is set to zero and registered as *total loss*. All transactions take place at the very moment the price of the benchmark is compared to the derived SMA.<sup>24</sup> We thus assume sufficient liquidity and an atomistic market.

### III.4 Evaluation Criteria for Trading Systems

The evaluation of an investment's success has to balance *risk* and *return*.<sup>25</sup> Performance measures bring together both components into a single key figure. Whereas the return part is rather easy to measure,<sup>26</sup> the risk component is much harder to interpret. This leads to a vast amount of different risk and performance measures (cf. Le Sourd (2007) or Cogneau & Hübner (2009) for an overview). For the analyses, we use a rich selection of different risk and performance measures [cf. table (3)], including the (higher) moments of the return distribution, the concept of stochastic dominance, Sharpe-, Sortino-, Calmar-, and Sterling ratios as well as

<sup>22</sup>A test over all SMA intervals between 5 to 200 shows that the changes between the levels develop rather smoothly. A finer grid therefore seems unnecessary.

<sup>23</sup>Basically, there are three possible standard implementations of a buying signal: trade one stock at its current price, trade an absolute position (i.e. a fixed amount), or trade a relative position to the portfolio size (i.e. a fixed ratio). Practitioners widely prefer absolute positions.

<sup>24</sup>In practice, one could assume that the price of the midday auction triggers the SMA and the system buys or sells at the very next price.

<sup>25</sup>Grinold & Kahn (2000) fittingly describe expected return as protagonist and risk as antagonist in the drama of active investments.

<sup>26</sup>We use log-returns for the analysis. We thus cannot allow losses above the initial investment. For the return and distribution calculations we then have to implement a virtual stop level if the initial investment is consumed by trading losses. The number of such paths are counted.

volatility, expected shortfall, semivariance, downside deviation, information ratio, tracking error and maximal- and mean drawdown. Besides, we evaluate trade statistics as generally used in practice<sup>27</sup> to capture the entire characteristics of the trading systems. Trade statistics comprise pure profit and loss figures like *gross profits* (accumulated profit of trades), *gross losses* (accumulated losses of trades), and the *total (net) result*, but also measure how success or failure develop. The *total number of trades* sheds light on the reactivity of the trading system: a high level of reactivity suggests fast adjustment on recent market developments but also a higher number of transactions, which may cause more whiplash signals and higher costs. The absolute *number of profitable trades*, and hence the *hit-ratio* (percentage of profitable trades), may be misleading regarding a trading system's quality,<sup>28</sup> but are important from a psychological viewpoint. The same holds true for the measure *longest sequence of losses*. Conversely, the ratio of the size of an *average profit trade* compared to the *average loss trade* is the key for success of a trend-following technical trading system.<sup>29</sup>

As side-result of our study, it turned out that the different measures mostly delivered comparable information. Even measures which are especially designed for highly non-normal (reshaped) distributions do not rank investment alternatives differently than standard measures, a result in-line with literature. Eling & Schuhmacher (2005), for instance, report similar findings for hedge funds. Hence, we focus on expected excess return, volatility and Sharpe ratio and only report additional figures in case of particular interest.<sup>30</sup>

When discussing return distributions, one has to distinguish clearly between the distribution of terminal results on the one hand, which describes the investor's exposure; and the distribution of the daily returns of a single path ("pathwise distribution") on the other (cf. figure (1)). Standard backtests, which are especially popular in practice, are only based on the single historical price path and thus deliver only a pathwise distribution, resulting in a mere estimate for the terminal result distribution. Especially if the distributions are skewed and reshaped, the pathwise distributions may be biased. Due to the simulation approach, we are able to analyze the terminal distribution, which delivers our main findings. Some key figures are nevertheless path-dependent; we then report the mean over all generated paths. For the historical simulation, the reshuffling technique allows a rather high precision but also leads to lower variety of extreme

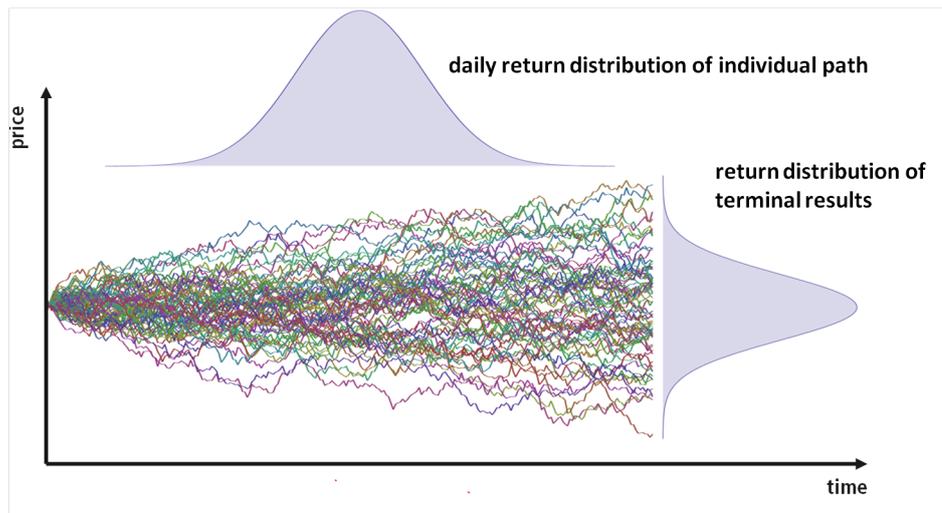
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<sup>27</sup>The analysis of trade statistics is based on Wagner (2003) and Cognitrend (2009).

<sup>28</sup>Practitioners act on the assumption that even profitable trend-following systems generally have hit-ratios lower than 50%.

<sup>29</sup>The average profit trade should be higher the lower the hit ratio. For example, Faber (2007) reports a seven times larger size of an average win trade compared to an average loss trade. Similarly, the average duration of a trade that ends up with a profit (*average duration of profit trade*) should be explicitly longer than the *average duration of a loss trade* to comply with the practitioners' rule: "cut your losses short".

<sup>30</sup>The complete results are available upon request.



**Figure 1: Different return distributions.** The relevant return distribution of an investment strategy is the distribution of terminal results. It may be estimated from the daily returns of an individual path. However, biases may occur in case of asymmetrically reshaped return distributions.

paths.<sup>31</sup> We here depend on the measures estimated from the pathwise distributions. However, in our parameter based simulations, we can compare the results from the terminal distribution with those from the pathwise daily return distributions. This provides a good indication of the potential bias between both distributions.<sup>32</sup>

## IV Simulation Results

In a nutshell, our results show that the SMA trading rule benefits from negative trends, high autocorrelation levels, and low volatility of the benchmark; heteroscedasticity has a rather small impact on timing results. These findings are based on parameterized stochastic processes but also systematically explain the timing performance in the historical bootstrap approach using real world data. No market inefficiency is necessary to generate timing success. Our results are still completely in-line with the empirical findings in recent literature, but considerably contradict their explanation attempts.

As an additional result, we conclude that timing is generally not a risk-reducing technique as sometimes has been suspected. Then again, timing strategies tend to increase all higher moments of the return distribution and especially the tail risks. Although timing may avoid large drawdowns, especially in bear markets, and largely provides protection against big single

<sup>31</sup>This is due to the predetermined randomness, since the historical bootstrap relies on the single observed path.

<sup>32</sup>As a side effect, this also suggests the level of distortion that typical backtests suffer from.

loss trades,<sup>33</sup> it may also suffer from *bleeding out* due to constant unlucky re-investing.<sup>34</sup> With respect to the very favorable results of timing strategies reported by Faber (2007), we agree with Marmi et al. (2009): Faber’s results lie well within the statistical variability of the returns and therefore cannot prove significant added-value.

## IV.1 Trends

In order to analyze the influence of the drift component on SMA timing results, we use a discretized geometric Brownian motion. Three different drift levels are analyzed, which represent the maximum (22.6% p.a.), the mean (5.2% p.a.), and the minimum (-11.6% p.a.) found in the dataset.<sup>35</sup> All drift levels are combined with the empirical mean volatility level of 26% p.a. Tables (4) to (7) contain the detailed results.

**Return Distribution Analysis** The timing results displayed in table (4) and figure (2) reveal a strong impact of the applied drift level. The higher the drift the worse the timing result. Only in case of negative drift (minimum level), the timing strategy earns a positive excess return. The positive drift levels (mean and maximum) – even when moderate – show a negative excess return. In all three cases, the strategy produces more volatility than the benchmark. Regarding the higher moments, the trading rule always skews the distribution to the left and causes fat left tails. This is confirmed by higher value-at-risk levels. The kurtosis of the timing return distribution is always higher than the benchmark’s. These effects are reflected by nearly all performance measures:<sup>36</sup> under mean and maximum drift, the trading rule underperforms the benchmark, while it outperforms under minimum drift. For positive trends, the timing strategy is even stochastically dominated by the buy-and-hold approach, while no dominance is found for negative drifts.

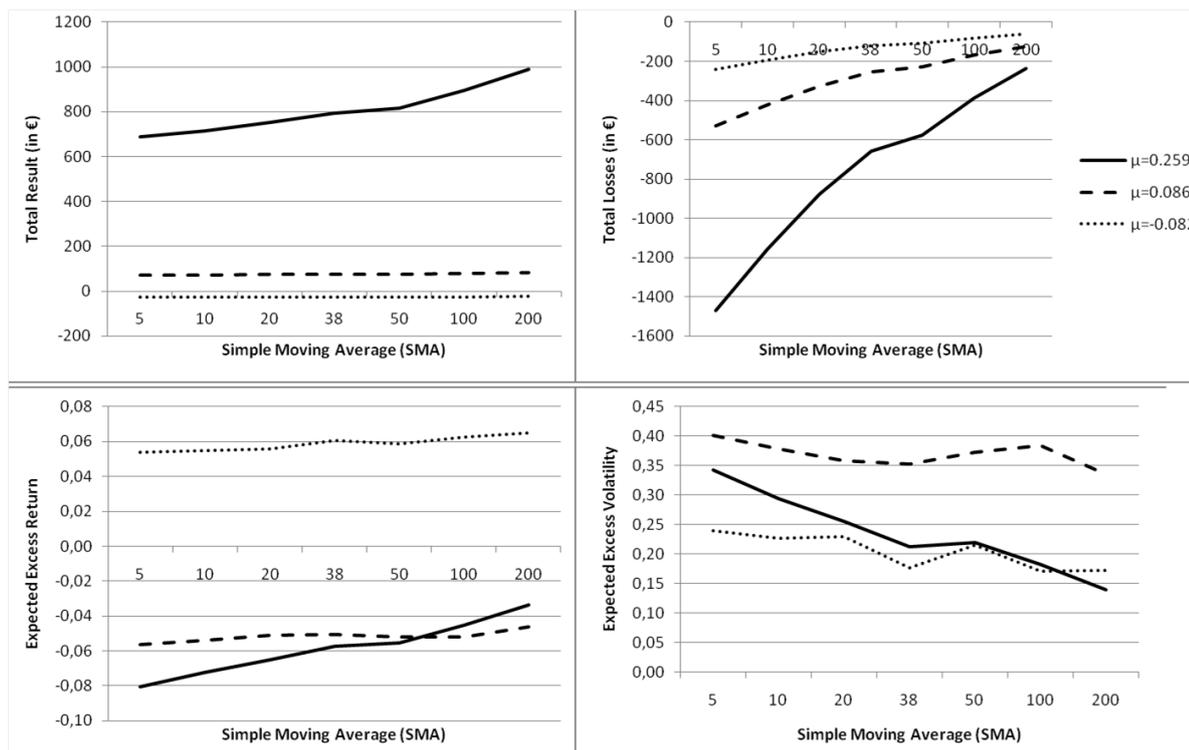
If the return distribution is estimated from the daily returns of individual paths, as in a classic backtest, then a significant bias emerges: expected excess returns and skewness are overestimated, whereas volatility and kurtosis appear too small. For a standard investor, who prefers high odd and low even moments, this is very problematic since the strategy appears too promising and the real risks may be severely underestimated. The discrepancy arises from the calculation method: if a path ends up low, its mean return is probably low, too. This implies that the real diffusion of all paths is significantly higher than estimated from an individual path.

<sup>33</sup>This complies with the practitioners’ rule “let your profits run and cut your losses short.”

<sup>34</sup>Comparable effects are known for stop-loss strategies.

<sup>35</sup>To correct for the volatility drag, the drifts  $\mu_e$  measured in the descriptive analysis must be transformed into  $\mu_a = \mu_e + \frac{1}{2} \cdot \sigma^2$  to generate the applied drift levels.

<sup>36</sup>The conditional Sharpe ratio on a 5% level is the only exception: here the timing rule outperforms under maximum and minimum drift of the underlying.



**Figure 2: Major results from trend component.** The more positive the trend component is, the higher the total (net) results from timing are. However, the total losses also increase with bullish drifts (estimated from daily returns). The expected excess return from timing, by contrast, is shrinking if the trend is positive. In all cases, timing increases the risk the investor has to bear (estimated from distribution of terminal results).

**Path Analysis** The results of the pathwise analysis are summarized in table (4). Interestingly, the total number of trades strongly depends on the interval of the SMA trading rule, but hardly on the strength of the trend component. As expected, a shorter SMA interval triggers more trades, indicating a higher level of reactivity. In the course of ten years, the SMA(5) trading rule triggers approximately 300 trades, the SMA(200) 45. The number of winner trades is, however, slightly higher in a bullish environment than in a bearish one. This is also reflected by the hit ratio, which is higher the stronger the trend component and the shorter the SMA interval. A hit ratio lower than 50% for trend-following trading systems also corresponds to traders' expectations. Even hit ratios lower than 20% may lead to positive total trading results, if the trend component is strong enough.

Total profits, total losses and total net results echo the findings reported above. At first glance, the increase of total losses for positive drifts is puzzling since one would expect less losses from whiplash signals in a bullish environment. However, total losses are an absolute measure, which becomes larger if prices are high. But a high positive drift quickly increases

the price level. Naturally, this also affects the size of the loss trades. Strong drifts thus lead to absolute higher losses. This is also confirmed by the size of the maximum loss trade.

According to Faber (2007), trading rules should provide a certain protection against price drops and hence high losses in an investor’s portfolio. The size of an average loss trade is indeed always considerably lower compared to an average profit trade; and the exposure time in a profit trade is notably longer than in a loss trade. One of the strongest points of the timing strategy is thus to follow the trader’s rule “let your profits run and cut your losses short.” But the protection gain from the SMA trading rule is modest at best: it cannot preserve the all-time-high levels of the equity curve if negative trends appear. Moreover, the system crucially depends on the high profit trades in falling markets: if the rebounds are not caught, profits are seriously affected. Trading systems may even suffer from severe drawdowns. Compared to the benchmark, timing increases the drawdown risk in case of positive drifts. Only for negative drift levels, high benchmark drawdowns are reduced. The longest loss sequences happen if negative drifts apply, however, i.e. the trading system produces lots of whiplash signals in anticipating potential trend reversals. Especially the longer SMA intervals are prone to long loss sequences.

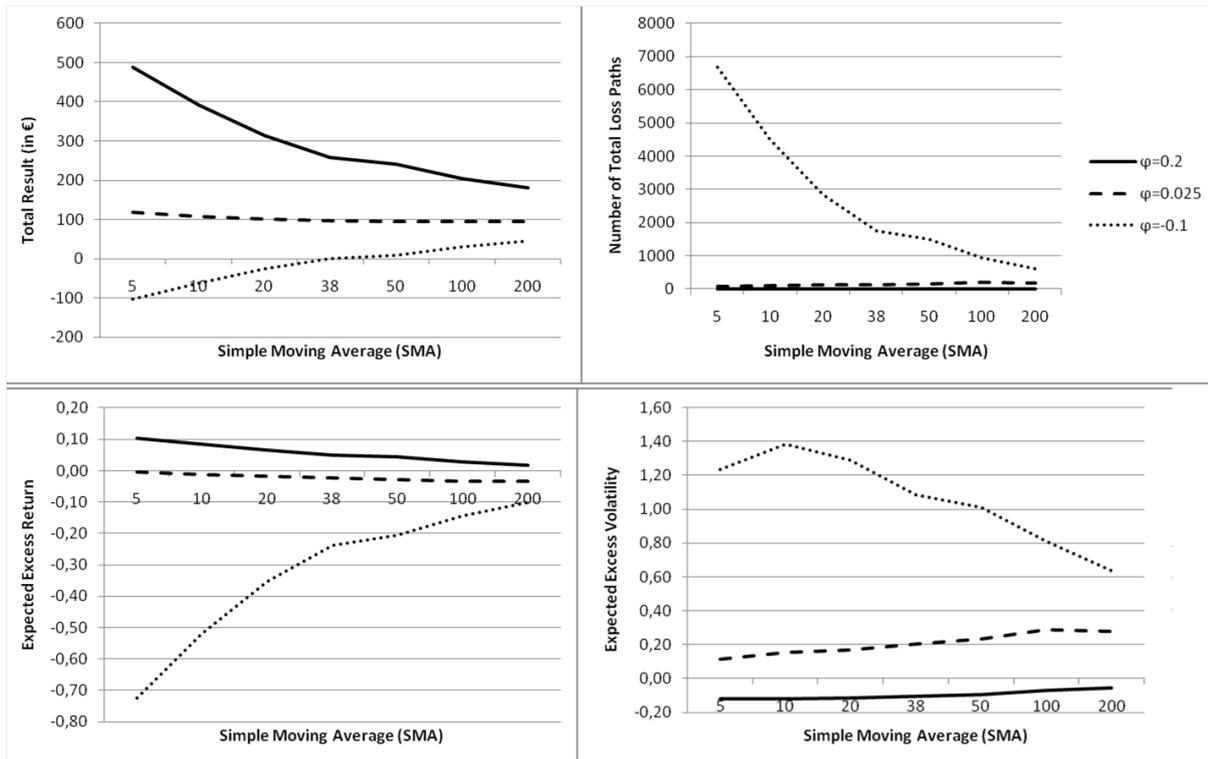
**Conclusions** The results confirm our first hypothesis that positive trends generally are not “your friend” when SMA timing strategies are applied. In this case, the trading system underperforms relative to the benchmark. The major risk factor is a failure to invest in a rising market.<sup>37</sup> By contrast, in a falling market disinvestment is beneficial. An interesting result is that timing generally comes at the price of increased higher moments, i.e. the risk rises. Only in case of negative drifts, timing actually generates risk-adjusted excess returns. It is thus not surprising that SMA timing strategies sometimes show impressive excess returns in certain market environments. They do not generate a superior return distribution, however. The performance does not indicate any prediction power for anticipating market trends.

## IV.2 Autocorrelation of Returns

In order to analyze the relevance of autocorrelation, we use an AR(1) process to generate autocorrelated return series. In all simulations, the drift is set at the empirical mean return level of 5.2% p.a. and the volatility at the empirical mean volatility level of 26% p.a.<sup>38</sup> We examine three different lag-one autocorrelation levels: the maximum (0.2064), the mean (0.025), and the minimum (-0.1027) of the empirical estimates from the dataset. An overview of the results can be found in tables (8) to (11) and figure (3).

<sup>37</sup>This is due to the construction of the trading system with its maximum degree of investment of  $\Delta - 1$ .

<sup>38</sup>Once more, the applied drifts have to be corrected with  $\mu_a = \mu_e \cdot (1 - \varphi)$ ; and the volatilities  $\sigma_a = \sigma_e^2 \cdot (1 - \varphi^2)$ .



**Figure 3: Major results from serial autocorrelation.** Positive serial autocorrelation clearly benefits the trading rule since the total result as well as the expected excess return increase (terminal return distribution). The risk of facing a total loss is also notably lower. In case of highly positive autocorrelation, the trading system even lowers the volatility of the equity curve (based on the distribution of terminal returns). However, if only moderate or even negative  $\varphi$  apply, then the portfolio's volatility is rising.

**Return Distribution Analysis** Compared to a non-autocorrelated underlying, a slightly positive autocorrelation (0.025) improves the results: mean returns from timing are higher (0.046 to 0.016 compared to -0.005 to 0.005) and the volatility lower (0.38 to 0.55 compared to 0.66 to 0.60). This effect is not strong enough to generate better results than the benchmark (mean return 0.051 and volatility 0.26), however. In addition, skewness and kurtosis are less favorable for investors. If the autocorrelation is set at the empirical maximum level, especially short-term SMA strategies attain excess returns over the benchmark, lower the volatility and skew the return distribution to the right. Only the kurtosis is still higher, indicating at least some paths that lead into a total loss (for SMA levels higher than 20). It seems that the timing strategy even stochastically dominates the benchmark.<sup>39</sup> By contrast, the penalty from negative autocorrelation is severe, especially for short SMA intervals: excess returns are highly

<sup>39</sup>There are too few extreme paths to check the tails with high precision.

negative, volatilities increase, the distributions become left skewed and the tails very fat. Those risk-return findings are also confirmed by the applied performance measures.

Interestingly, if positive autocorrelation is applied, then the expected excess return estimated from the pathwise daily return distribution seems to be a good estimator for the expected excess return from terminal results. In this environment, the daily return distribution is right skewed, which is favored by investors and compensates the bias.

**Path Analysis** If the mean autocorrelation level of 0.025 is applied, the trade statistics are very similar to those of the non-autocorrelated Brownian motion.<sup>40</sup> Using those values as standard of comparison, the results show that high positive levels of autocorrelation favor especially the short term SMA trading rules. Although about 16% less transactions are triggered, the number of wins is even slightly higher, which means fewer whiplash signals. This is also expressed by consistently higher hit ratios. On average, a trade yields between 1.51 € and 2.79 € (for the SMA(5) and the SMA(200) respectively) more compared to the mean autocorrelation level (on a basis of an initial investment of 100 €). While the size of an average loss trade is hardly affected by autocorrelation, the average profit trade is higher and thus drives the effect. The higher profits are achieved even in slightly less exposure time and the drawdowns are rather mild.

For negative autocorrelation, especially the short SMA intervals react highly sensitive and produce worse results. For example, the SMA(5) trading rule gains a total of 118.10 € with mean autocorrelation but loses -102.26 € with the negative one. Longer SMA intervals are less sensitive. In case of negative autocorrelation, slightly more trades are triggered but most of them seem to be whiplash signals, which is confirmed by a low hit ratio. The size of an average loss trade is still rather stable, again indicating an effective reduction of the loss per trade. The maximum sequence of loss trades is increased by negative autocorrelation as expected, and may also promote bleed-outs. What is more, maximum drawdowns may be disastrous.

**Conclusions** We clearly reject Tucker's (1992) hypothesis that trading rules cannot exploit autocorrelation in returns. Even moderate positive levels may improve the results. In case of positive autocorrelation, especially the SMA trading rules with short intervals benefit, though they suffer extremely if autocorrelation turns negative. The level of autocorrelation is thus an important impact factor for timing results. The mean level of autocorrelation detected in the 35 different markets is overall rather low and mostly leads only to minimal improvement of trading results.<sup>41</sup>

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<sup>40</sup>To be exact, they are very similar but slightly improve the trading results.

<sup>41</sup>Moreover, autocorrelation can hardly explain Faber's (2007) superior trading success, since he applied an SMA trading rule with a rather long interval (approx. 200 days), which reacts more or less insensitive to the degree of autocorrelation.

### IV.3 Volatility and Volatility Clustering of Returns

The influence of volatility on the success of trend-following technical trading rules is a controversial issue. Whereas Brock et al. (1992) suggest that there is no or at least only minimal impact, Neely (2003) assumes a positive,<sup>42</sup> and Dunis & Miao (2004) a negative one. To deconstruct this controversy, the discretized Brownian motion is again used with a mean drift level of 5.2% p.a. We initially check for different annual volatility levels: maximum 39%, mean 26%, and minimum 16% from the empirical dataset. A GARCH(1,1) process is then used to model volatility clustering. Here, the empirical mean level is applied, i.e.  $\alpha = 0.11$  and  $\beta = 0.87$ , which corresponds largely to the existing literature.<sup>43</sup> The results from the impact of volatility can be found in tables (12) to (15) and figure (4); those from clustered volatilities in tables (16) to (19) and figure (5).

**Return Distribution Analysis** Independent from the applied volatility level in the simulation, the timing strategy is neither able to generate positive excess returns nor to smooth the volatility of the benchmark: if high (0.39) or medium (0.26) volatility levels are applied, they produce huge excess volatility compared to the underlying. Only if the underlying's volatility is already low (0.16), the trading rule keeps the level stable. Hence, in times when smoothing is supposedly favored, it is not created. The initially puzzling observation that, although the mean of the return distribution is negative for high volatilities, the total net result is clearly positive [cf. fig.4] can be explained with the high number of paths (about 15%) which lead to a total loss or worse and hence deliver extremely negative return values in the log-return calculation. The left tail of the distribution shows a remarkable buckle. Another indication is the highly negative skew and the excess kurtosis. For lower volatilities, the effect becomes more pronounced.<sup>44</sup>

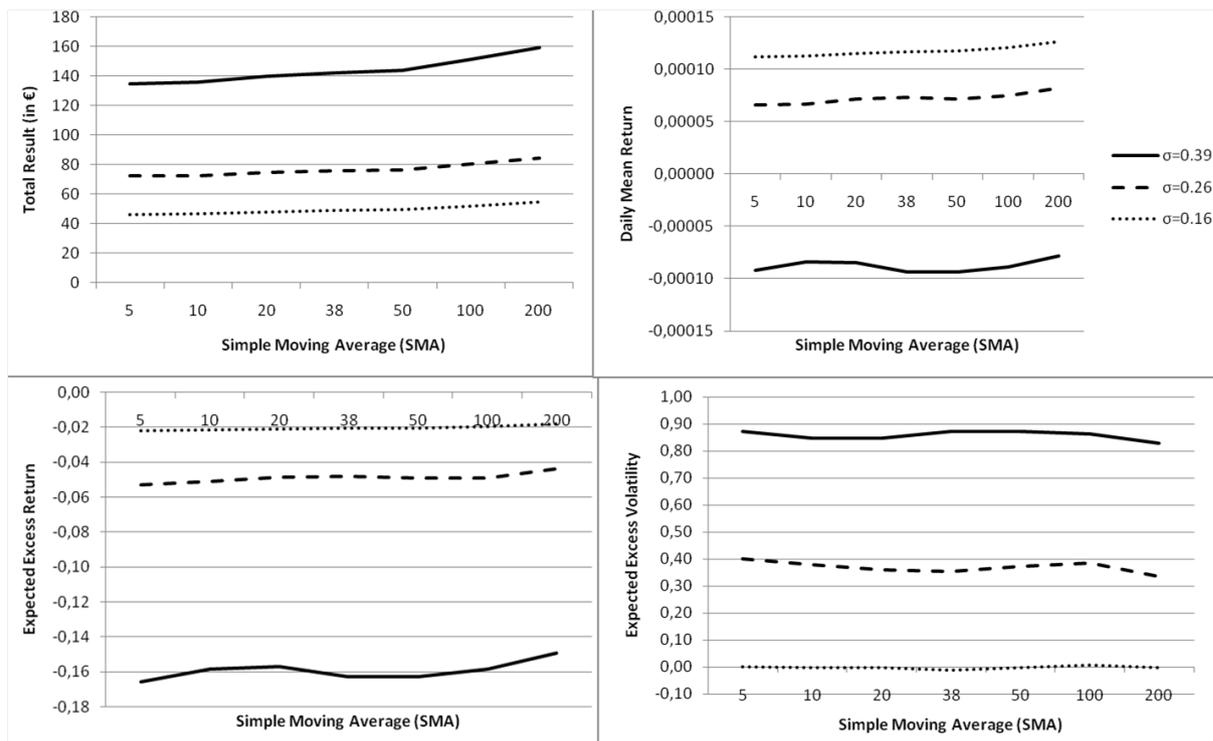
The trading rule seems to better cope with clustered returns, since the severe impact from high volatility levels is weakened: the mean returns of the trading systems are higher and the volatilities of the equity curves lower. This comes at the cost that the higher moments are more extreme than in the simulation with homoscedastic volatilities.

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<sup>42</sup>He argues that the trading strategies spend not all of the time in the market and hence should have less volatile returns than the corresponding buy-and-hold approach.

<sup>43</sup>We still have to cope with the drag effect: we adjust the mean drift of 0.052 by  $\mu_a = \mu_e + \frac{1}{2} \cdot \sigma_a^2$  with  $\sigma_a^2$  being the applied volatility level in the simulation. The intention was to measure the volatility effect on the timing result only, not the mixed influence including the effects of the drift component. We nevertheless checked for the unadjusted drifts, which produced the expected results: the timing result is also affected by volatility and the drift component.

<sup>44</sup>Considering the distribution of daily returns, it becomes clear that the estimates for the moments would be biased again. The medium volatility level, however, now delivers a positive mean return. This means that the expectation is too optimistic if the investor relies on the estimates from the daily returns.

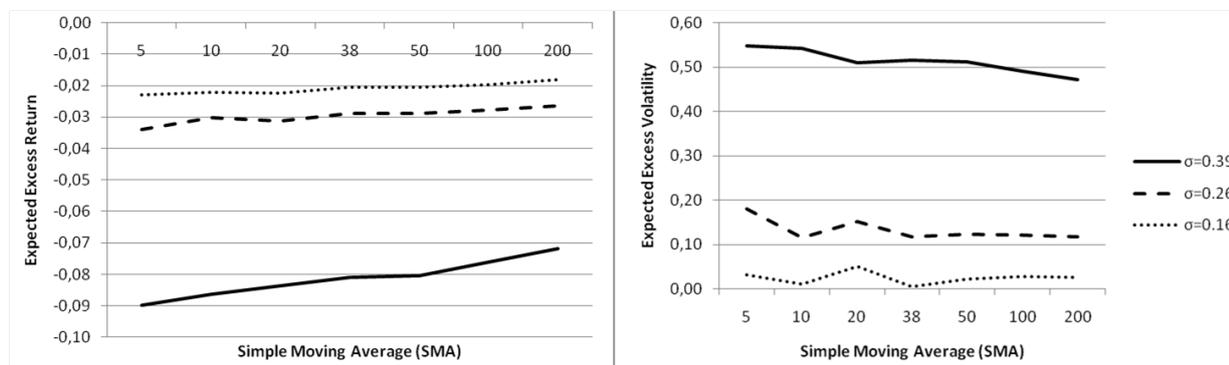


**Figure 4: Major results from volatility.** Rising volatility has a positive impact on total results, but a negative one on the daily mean returns due to a high number of paths that generate a total loss of the initial wealth. The lower the expected excess return, the higher the volatility of the underlying. Furthermore, the trading system is not capable to smooth high volatile benchmark returns.

**Path Analysis** The major result from the trade statistics is that gross profits and losses but also the total net result increase with rising volatilities. Higher volatility levels neither seem to raise the total number of transactions nor the number of losing trades. This is surprising since one may suspect more volatile markets to trigger more whiplash signals. The same findings hold for the average duration of win or loss trades and the maximum sequence of consecutive losses, which are stable over the different volatility levels. The volume of trades, however rises indicating a higher exposure in the trading position from increased volatility levels. A high volatility also increases the expected maximum drawdowns, i.e. the trading rule is not able to protect the investor from large peak-to-valley moves. Finally, it should be noted that in less volatile markets, the system is more often invested in the risky asset, especially for long SMA intervals.

In case of clustered volatilities, profits as well as losses are considerably dampened whereas the number of transactions, the hit ratio, the trade durations, and the maximum sequence

of consecutive losses seem unaffected. The shrinking effect is especially pronounced for high volatility levels and diminishes for lower ones.



**Figure 5: Major results from volatility clustering.** In case of highly volatile and heteroscedastic underlyings, the expected excess returns and the expected excess volatility of the timing portfolio improve compared to the simulation where volatilities are not clustered. For low volatile benchmarks, the impact from clustering diminishes.

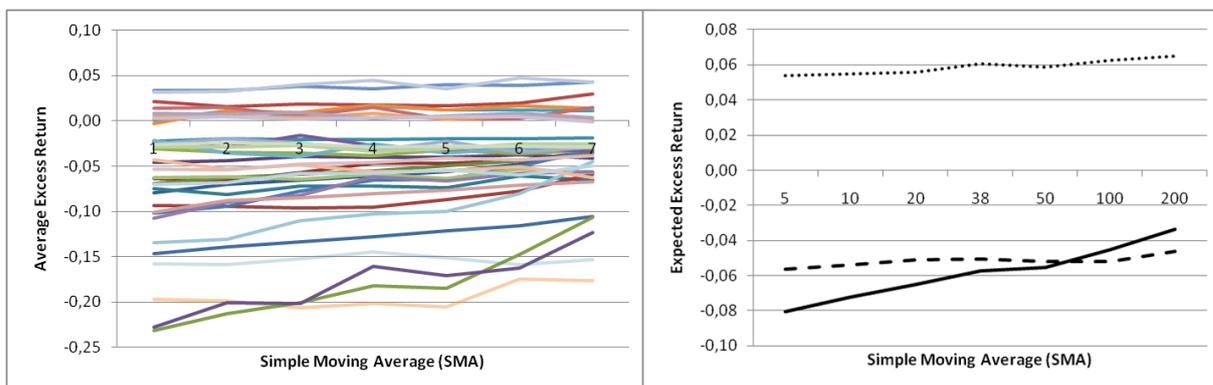
**Conclusions** In general, high volatility in the simulated price paths decreases the expected excess return of timing compared to the benchmark and increases the other moments in the equity curve, which indicates a negative impact of volatility on timing. It should be noted, however, that the total net result increases with rising volatility. The reason for this effect is the number of paths that lead to a total loss of the initial investment. Those contrary results might explain the different hypotheses found in the literature. Since timing is not capable of reducing the input volatility and rather biases the distribution in a unfavorable way for investors, we agree with Dunis & Miao (2004). The trading rule always underperforms the benchmark, no matter which performance measure is applied.

The introduction of heteroscedastic volatilities, however, seems to benefit the trading rule compared to the homoscedastic setting, especially in a high volatile environment. This finding seems to be intuitive since the periods of high volatilities are compressed over time, meaning that the periods in which the systems suffer are shorter.

#### IV.4 Market Status and Efficiency

Based on our findings from the parameterized simulations, we would expect SMA timing rules to generate excess returns in markets with negative drifts and low volatility and vice versa. Therefore, Belgium, England, Europe (i.e. DJ Euro Stoxx 50), France, Italy, Japan, Spain, Switzerland, and the U.S.A. should provide a very favorable environment for the trading rule

during the time period of our data sample. Germany, Greece, Sweden, and the Netherlands follow to a slightly lesser extent. The worst timing conditions are provided by Argentina, Brazil, China, Hong Kong, Hungary, India, Poland, Russia, Saudi Arabia, South Korea, and Turkey. These predictions are based on a simple scoring model: depending on the stochastic parameters of the historical time series, an index is assigned two points for a negative drift, one point for below average volatility and 0.5 points for above average clustering of returns. These weightings reflect the importance of the parameters as found in our study. The scoring results are displayed in table (20). Incidentally, in our data sample, the developed countries provide better timing chances than the emerging ones, which is solely based on the properties of the price series. Nevertheless, our prediction stands in contrast to the suggestions of recent literature. To verify our forecast, the sample of all 35 leading equity indices is used to run non-parametric historical bootstraps over a time horizon of ten years (i.e. 2500 trading days). Tables (21) to (29) show the detailed results from the bootstrap simulations.



**Figure 6: Comparison of results based on simulation and real market data.** The left graph shows the average excess return of each of the 35 different countries. The right graph displays the expected excess return from a geometric Brownian motion based on different drift levels. There is a clear relation between the trend of the underlying benchmark and the timing success in terms of excess return: the higher the mean daily return in the asset price series, the lower the mean excess return from timing.

As a first result, we found that our predictions based on the scoring are pretty accurate: England, Europe, France, Italy, Japan, Switzerland, the Netherlands, and the U.S. show excess returns<sup>45</sup> over all SMA levels; in the Greek market, the trading system achieved excess returns in most of the SMA intervals (with the SMA(5) as the only exception). Belgium and Spain generated slightly negative excess returns, which still seems acceptable from an explanatory point of view (their negative trends were not very strong). The worst results were delivered in

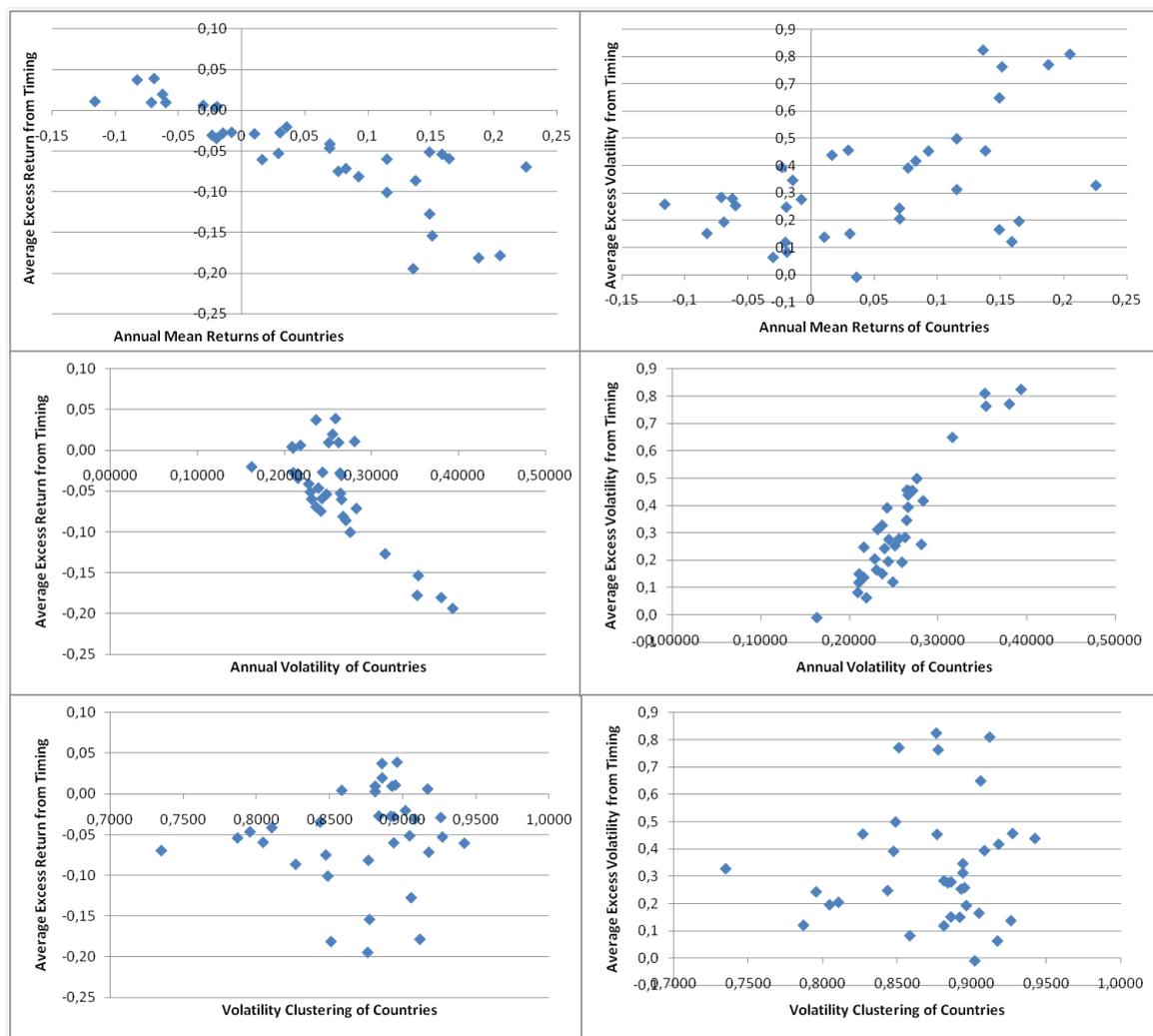
<sup>45</sup>The excess return is derived as average over all bootstrapped paths.

Argentina, Brazil, China, Russia, Saudi Arabia, and Turkey — again perfectly in-line with our forecasts. Hong Kong, Hungary, India, Poland, and South Korea also generated negative excess returns as expected.

**Regression Analysis** In order to analyze the influence of the asset price characteristics on the timing results in more detail, we regress excess return, excess volatility, and excess Sharpe ratio onto the parameters drift  $\mu$ , volatility  $\sigma$ , heteroscedasticity  $\beta$ , skewness, and kurtosis. Tables (30) to (36) and figure (7) show the most important results. The regression analysis confirms our hypothesis that the drift component has a significant impact on the excess returns from timing: dependent on the SMA interval, the  $R^2$  lies between 0.72 and 0.54 (for the SMA(200) and SMA(5) respectively). For the risk-adjusted excess returns (Sharpe ratio), the  $R^2$  values are even higher (0.97 to 0.71). But also the underlying's volatility has a significant impact on timing results: regarding its influence on excess returns, the  $R^2$  shows levels between 0.57 and 0.53; on excess volatility, the values are between 0.78 and 0.72. Additionally, heteroscedasticity reveals a significant dependence to the excess Sharpe ratio, at least besides the SMA(200). This confirms our hypothesis that the timing results are largely explainable by certain asset price properties of the underlying benchmark.

**Path Analysis** In nearly all markets, timing clearly raised the volatility of the equity curve compared to the benchmark, with Australia as the only exception. Similar findings hold for higher moments: skews were generally lowered and the kurtosis raised, indicating increased risk and thus an unfavorable reshaping for investors. On drawdown protection, our results show a decrease of the maximum drawdown in at least 15 out of 35 markets. In most cases, even the reduced drawdowns are still catastrophic, so that we cannot recognize a real protection effect. Only in three markets, the maximum peak-to-valley moves are lowered to acceptable levels: England, Switzerland, and the U.S. The key figures of the trade statistics are generally rather close to the expectations from the results on simulated data derived beforehand. The longer SMA intervals show more divergences, probably because they are based on less transactions, but the results for the short term SMAs lie within a close range. Only Austria, Peru, and Saudi-Arabia show explicitly higher hit-ratios and longer investment times in the risky asset. They also show more favorable ratios of the mean size of win versus loss trades and its duration, albeit without performance advantages.

Our mean hit ratio lies around 17.3%. If we compare this to the findings reported by Faber (2007), his 54% level seems uncharacteristically high. The maximum we found on average was 26% (Saudi Arabia). For a long term SMA, however, a hit ratio of more than 55% is achievable in principle. We found it sporadically in some paths. Similar findings hold for the amount of time the system is invested in the risky asset: our figure (55.8%) is lower than Faber's (70%), though it still is within the empirical range. By contrast, our number of round trips per year



**Figure 7: Major results from historical bootstraps.** The scatter plots show the interrelations between asset price parameters of the benchmark's time series and the timing result. Timing benefits from negative drifts since it generates excess returns and lowers the volatility of the equity curve. Highly volatile asset prices also lead to lower excess returns and increases volatility in the timing portfolio. Different levels of volatility clustering have a minor impact on timing results. If volatilities are high in the benchmark, however, stronger clustering should be preferred.

is slightly higher: we estimated 4.5 in comparison to 3-4. In Faber's system, the duration of an average win trade is six times longer than a loss trade, which is lower than our finding of 17 times on average; the ratio of the win trade's size to a loss trade is, however, approximately the same (seven times).

**Conclusions** Our study on the basis of real data clearly confirms the hypothesis that the asset price characteristics of the underlying price process have a crucial impact on timing results. This allows us to forecast the timing success depending on the market's parameters. An OLS regression analysis supports our predictions and verifies our assumption that the drift has the strongest influence on timing success. By contrast, the higher moments (skewness, kurtosis) seem not to have any significant impact on the timing result in the empirical sample. As we presumed, the level of market development, and hence the degree of efficiency, does not play any role. Trading worked coincidentally rather well in the developed world and quite poorly in the emerging markets. The driving factor for the timing success is the parametric environment the trading system stumbles on.

## V Summary

Recent academic studies widely acknowledge that some technical trading rules are able to produce (risk-adjusted) excess returns. With rather vague reasoning, the authors largely conclude that either hidden patterns in the price data or insufficient market efficiency allow for predictability. The forecasting ability often disappears when the trading rule is applied to out-of-sample price data. This effect is typically attributed to improved market efficiency. Our study contributes to the discussion by providing a structured analysis of the relevance of the most important price process parameters. As a result, the traditional explanations for timing success can be abandoned: we find that it is very likely for the SMA trading rule to generate excess returns over its benchmark if the underlying price path exhibits negative drifts, high serial autocorrelation, low volatilities of returns, and highly clustered volatilities. Drift and autocorrelation of the underlying asset seem to have the largest impact, though. Our findings are confirmed by non-parametric historical simulations on real data, in which we can predict timing success by a simple scoring of the data sample's process parameters; we additionally run an OLS regression analysis. The main result is that the degree of development and hence market efficiency does not have any impact on the result of a technical timing strategy, which contradicts standard explanations. It should be noted, though, that we could not test the influence of serial autocorrelation on historical data due to limitations of the simulation approach and the length of the available time series. Although especially the emerging markets show higher serial autocorrelation levels, they are typically not high enough to explain successful timing.

With regards to the loss protection potential of timing strategies, propagated by some authors, we do not see a distinctive protection element in general: in bear market periods trading rules might indeed preserve the active managed portfolio from extreme drawdowns, but at the price of increasing other risks for the investor (measured by a wide range of different risk fig-

ures). Since the trading rule is not capable of predicting bear markets but only exploits favorable market parameters, the main risk for the investor is a bleed-out, i.e. frequent small loss trades, which consume the initial wealth and hence also lead to distinctive drawdowns in the portfolio. Moreover, it is worth noting that potential losses from timing are by far higher than potential wins, which is in-line with Sharpe (1975).

Referring to Kostolany's suggestion, we find that perfect timing is most certainly a dominant investment strategy. However, at least the simple SMA trading rules do not offer such properties. We frankly do not see any prediction power but only a systematic reaction to the stochastic properties of the asset price process. The fitting of a timing strategy to past price data thus seems to be tantamount to Sharpe's image of fighting a future war with past strategies.

## Acknowledgments

We are grateful to Thomas Heidorn and Wolfgang M. Schmidt from Frankfurt School of Finance & Management for helpful suggestions. The dataset from Thomson Reuters is very much appreciated. Furthermore, we want to thank the members of the Centre for Practical Quantitative Finance and the participants of the research colloquium at the University of Regensburg as well as the attendees of the 24th European Conference on Operational Research (Lisbon, Portugal), the 2010 International Conference on Applied Operational Research (Turku, Finland), the 2010 International Conference of Operations Research (Munich, Germany), and the 8th Research Conference Campus for Finance (Vallendar, Germany) for comments and feedback. We would also like to thank the 8th Research Conference Campus for Finance at WHU for awarding us the WHU Finance Award for the third best paper.

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## Appendix

Country	Index	RIC	Region	Market Status	Remark
Argentina	MERVAL	.MERV	South America	Frontier Emerging	
Australia	All Ordinaries	.AORD	Oceania	Developed	
Austria	ATX	.ATX	Central Europe	Developed	
Belgium	BEL-20	.BFX	Western Europe	Developed	
Brazil	BOVESPA	.BVSP	South America	Advanced Emerging	BRIC
Canada	S&P TSX 60	.TSE60	North America	Developed	
China	HSCE	.HSCE	East Asia	Secondary Emerging	BRIC
Europe	DJ EuroStoxx 50	.STOXX50E	Europe	Developed	
France	CAC 40	.FCHI	Western Europe	Developed	
Germany	DAX 30	.GDAXI	Central Europe	Developed	
Greece	Athex 20	.ATF	Southeast Europe	Developed	
Hong Kong	Hang Seng	.HSI	East Asia	Developed	
Hungary	BUX	.BUX	Eastern Europe	Advanced Emerging	
India	S&P CXN NIFTY	.NSEI	South Asia	Secondary Emerging	BRIC
Indonesia	JSX Composite	.JKSE	Southeast Asia	Secondary Emerging	Next 11
Italy	MIB 30	.FTMIB	Southern Europe	Developed	
Japan	Nikkei 225	.N225	East Asia	Developed	
Mexico	IPC	.MXX	Central America	Advanced Emerging	Next 11
The Netherlands	AEX	.AEX	Western Europe	Developed	
Pakistan	KSE 100	.KSE	South Asia	Secondary Emerging	Next 11
Peru	Lima General Index	.IGRA	South America	Secondary Emerging	
The Philippines	PSEi	.PSI	Southeast Asia	Secondary Emerging	Next 11
Poland	WIG 20	.WIG20	Eastern Europe	Advanced Emerging	
Russia	RTS	.IRTS	Eastern Europe	Secondary Emerging	BRIC
Saudi Arabia	Tadawul FF Index	.TASI	Arabia	n/a	
Singapore	STI	.FTSTI	Southeast Asia	Developed	
South Africa	JSE Top 40	.FTJ20USD	Africa	Advanced Emerging	
South Korea	KOSPI	.KS11	East Asia	Developed	Next 11
Spain	IBEX 30	.IBEX	Southwest Europe	Developed	
Sweden	OMX Stockholm 30	.OMXS30	Northern Europe	Developed	
Switzerland	SMI	.SSMI	Central Europe	Developed	
Thailand	SET	.SETI	Southeast Asia	Secondary Emerging	
Turkey	ISE 100	.XU100	Arabia	Secondary Emerging	Next 11
United Kingdom	FTSE 100	.FTSE	Western Europe	Developed	
U.S.A.	S&P 500	.GSPC	North America	Developed	

**Table 1: The selection of 35 leading equity indices.** The table shows the 35 selected countries as well as their corresponding leading equity index. Moreover the geographical location is given. All data is taken from Thomson Reuters. RIC denotes the Reuters Instrument Code. The rating of the market status is taken from the FTSE list and divided into four classes: developed, advanced emerging, secondary emerging and frontier markets.

Country	$\mu$	$\sigma$	skew	kurt	JB(p)	$\varphi$	$\alpha$	$\beta$	$\omega$
Argentina	6.05E-04	0.02240	-0.0577	7.74	0.001	0.0426	0.0975	0.8775	1.16E-05
Australia	1.44E-04	0.01030	-0.6469	10.23	0.001	-0.0332	0.0939	0.9021	6.96E-07
Austria	3.08E-04	0.01532	-0.3286	11.43	0.001	0.0529	0.1370	0.8476	3.56E-06
Belgium	-7.85E-05	0.01366	0.0430	9.58	0.001	0.0645	0.1478	0.8436	2.33E-06
Brazil	5.97E-04	0.01999	-0.1052	6.74	0.001	0.0056	0.0671	0.9060	9.74E-06
Canada	4.20E-05	0.01365	-0.6975	12.10	0.001	-0.0828	0.0692	0.9263	8.37E-07
China	8.20E-04	0.02232	0.0289	8.34	0.001	0.0746	0.0816	0.9120	3.67E-06
Europe	-2.50E-04	0.01618	0.0715	7.71	0.001	-0.0549	0.1081	0.8861	2.16E-06
France	-2.39E-04	0.01588	0.0945	8.33	0.001	-0.0545	0.1023	0.8929	1.88E-06
Germany	-5.82E-05	0.01672	0.0458	7.42	0.001	-0.0393	0.0993	0.8940	2.24E-06
Greece	-4.64E-04	0.01777	-0.0031	7.26	0.001	0.0879	0.0996	0.8951	2.77E-06
Hong Kong	1.18E-04	0.01675	0.0482	10.80	0.001	-0.0233	0.0679	0.9274	1.35E-06
Hungary	3.72E-04	0.01694	-0.0608	9.15	0.001	0.0678	0.0995	0.8767	6.40E-06
India	5.53E-04	0.01715	-0.3047	10.75	0.001	0.0800	0.1492	0.8269	8.42E-06
Indonesia	6.59E-04	0.01540	-0.6360	8.77	0.001	0.1251	0.1341	0.8046	1.47E-05
Italy	-3.30E-04	0.01498	0.0380	9.50	0.001	-0.0100	0.1101	0.8860	1.62E-06
Japan	-2.76E-04	0.01639	-0.3009	9.11	0.001	-0.0356	0.0943	0.8963	2.89E-06
Mexico	5.97E-04	0.01456	0.0355	7.30	0.001	0.1038	0.0769	0.9049	3.66E-06
The Netherlands	-2.85E-04	0.01661	-0.0356	8.72	0.001	-0.0259	0.1146	0.8813	1.81E-06
Pakistan	6.36E-04	0.01573	-0.2356	5.51	0.001	0.1007	0.1700	0.7871	1.13E-05
Peru	9.03E-04	0.01497	-0.3824	13.50	0.001	0.2064	0.2410	0.7350	6.99E-06
The Philippines	2.81E-04	0.01444	0.5627	19.16	0.001	0.1195	0.1219	0.8106	1.52E-05
Poland	6.62E-05	0.01683	-0.0660	4.80	0.001	0.0463	0.0500	0.9424	2.28E-06
Russia	7.52E-04	0.02407	-0.4505	11.56	0.001	0.0933	0.1241	0.8511	1.37E-05
Saudi Arabia	4.62E-04	0.01745	-0.9722	10.99	0.001	0.0477	0.1511	0.8489	2.86E-06
Singapore	1.23E-04	0.01332	-0.1447	6.99	0.001	0.0146	0.1026	0.8920	1.66E-06
South Africa	4.62E-04	0.01465	-0.0542	6.15	0.001	0.0388	0.0912	0.8941	3.22E-06
South Korea	3.32E-04	0.01790	-0.4825	7.35	0.001	0.0172	0.0752	0.9180	2.73E-06
Spain	-3.09E-05	0.01545	0.1533	9.39	0.001	-0.0329	0.1110	0.8839	2.12E-06
Sweden	-9.24E-05	0.01681	0.1360	6.14	0.001	-0.0259	0.0861	0.9085	2.03E-06
Switzerland	-7.66E-05	0.01323	0.0254	9.10	0.001	0.0084	0.1298	0.8585	2.34E-06
Thailand	2.80E-04	0.01514	-0.7080	12.29	0.001	0.0299	0.1053	0.7956	2.16E-05
Turkey	5.45E-04	0.02490	-0.0271	9.43	0.001	0.0069	0.1062	0.8762	1.22E-05
United Kingdom	-8.17E-05	0.01330	-0.1267	9.63	0.001	-0.0733	0.1148	0.8813	1.22E-06
U.S.A.	-1.21E-04	0.01384	-0.0985	11.03	0.001	-0.1027	0.0765	0.9172	1.12E-06
Minimum	-4.64E-04	0.0103	-0.9722	4.80	0.001	-0.1027	0.0500	0.7350	6.96E-07
Maximum	9.03E-04	0.0249	0.5627	19.16	0.001	0.2064	0.2410	0.9424	2.16E-05
Mean	2.08E-04	0.0164	-0.1612	9.26	0.001	0.0240	0.1088	0.8739	5.28E-06

**Table 2: Descriptive statistics of 35 leading equity indices.** For the daily returns, the table displays the descriptive statistics (mean  $\mu$ , standard deviation  $\sigma$ , skew and kurtosis of the return distribution) as well as the autocorrelation parameter  $\varphi$  for the estimated AR(1) process. Furthermore, the estimated return autocorrelation  $\alpha$ , volatility autocorrelation  $\beta$ , and mean level volatility  $\omega$  for the GARCH(1,1) process are given. JB(p) denotes the p-value of the Jarque-Bera test on normality.

**Table 3: Overview on applied evaluation criteria.** For the analyses, a rich selection of different evaluation criteria is applied. It turns out, though, that the different criteria largely point in the same direction. The results of the study are hence based on the relevant findings only.

<b>Criterion</b>	<b>Brief Description</b>
<b><u>Trade Statistics</u></b>	
<b>Profits and Losses</b>	
Sum of profits	Accumulated individual profit trades of the trading system
Sum of losses	Accumulated individual loss trades of the trading system
Total (net) result	Net profit or loss of the trading system
Biggest win	Biggest single profit trade of the trading system
Biggest loss	Biggest single loss trade of the trading system
Average win trade	Mean of the individual profit trades
Average loss trade	Mean of the individual loss trades
Average trade	Mean of all trades
Best result	Best timing result over all paths
Worst result	Worst timing result over all paths
Average result	Mean timing result over all paths
<b>Trades</b>	
Number of transactions	Total number of all open and closing transactions
Number of profits	Total number of individual profit trades
Number of losses	Total number of individual loss trades
Hit ratio	Total number of profit trade divided by total number of trades
<b>Equity Curve Analysis</b>	
All-time-high	Price and point in time of all-time-high
All-time-low	Price and point in time of all-time-low

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<b>Criterion</b>	<b>Brief Description</b>
<b><u>Psychological key figures</u></b>	
Maximal drawdown	Maximal distance between global peak and valley of price path
Mean drawdown	Mean distance between local peaks and valleys of price path
Longest sequence of losses	Longest series of loss trades
Average duration of a profit trade	Mean time of investment in a profit trade
Average duration of a loss trade	Mean time of investment in a loss trade
<b><u>Return distribution measures</u></b>	
Mean of returns	First moment of return distribution
Median of returns	Numeric value separating the probability distribution in two halves.
Skew of returns	Third moment of return distribution
Kurtosis of returns	Fourth moment of return distribution
<b><u>Risk measures</u></b>	
Variance	Second moment of return distribution
Volatility	Standard deviation of returns
Expected shortfall	Expresses the expected loss with respect to an individual threshold
Semivariance	Defined as expected squared shortfall
Downside deviation	Square root of the semivariance, which corresponds to “downside” counterpart of the standard deviation
Tracking error	Standard deviation of the difference between the portfolio and benchmark returns
<b><u>Expected excess measures</u></b>	
Expected excess return	(based on terminal distribution, compared to benchmark) Expected over return from timing
Expected excess volatility	Expected higher volatility in the equity curve

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<b>Criterion</b>	<b>Brief Description</b>
<b><u>Performance measures</u></b>	
Sharpe ratio	Ratio of return to standard deviation
Sortino ratio	Ratio of return to downside deviation
Calmar ratio	Ratio of returns to maximum drawdown
Sterling ratio	Ratio of returns to (increased) adjusted maximum drawdown
Information ratio	Ratio of residual return to residual risk
Omega ratio	Ratio of probability-weighted profits to probability-weighted losses with respect to an individual threshold
RINA index	Combines the total result, the time in the market and mean drawdown to a reward-risk ratio
<b><u>Sequence analysis of timing</u></b>	
Runs analysis	Test if timing returns are stochastic
Autocorrelation	Serial autocorrelation of first lag of timing returns
<b><u>Miscellaneous</u></b>	
Stochastic dominance	Form of stochastic ordering that requires only limited preference assumptions

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$\mu$	SMA	Tot.Profit	Tot.Loss	Net Result	Av.Profit	Av.Loss	Av.Trade	Max.Win	Max.Loss	No.Trades	No.Win	No.Loss	Hit Ratio	TiM
0.259	5	2159.46	-1470.79	688.67	19.62	-7.82	2.34	179.16	-49.87	299.3	108.1	191.2	0.3617	0.54
0.259	10	1869.79	-1156.94	712.85	26.31	-8.22	3.43	217.53	-49.32	213.1	69.6	143.5	0.3276	0.56
0.259	20	1628.97	-877.74	751.23	36.31	-8.44	5.20	270.84	-47.72	150.7	44.0	106.7	0.2937	0.58
0.259	38	1451.60	-657.33	794.26	50.62	-8.58	7.88	335.16	-45.07	107.7	28.4	79.4	0.2662	0.61
0.259	50	1391.14	-575.09	816.05	58.99	-8.61	9.52	368.27	-43.73	93.1	23.5	69.6	0.2557	0.63
0.259	100	1281.59	-386.87	894.72	92.07	-8.43	16.44	481.23	-38.49	63.4	14.4	49.0	0.2338	0.68
0.259	200	1227.34	-236.33	991.01	161.45	-8.38	34.58	642.23	-31.04	40.3	8.7	31.6	0.2302	0.74
0.086	5	600.61	-528.46	72.15	5.92	-2.65	0.25	38.99	-11.78	301.1	99.6	201.5	0.3313	0.51
0.086	10	493.86	-421.35	72.51	7.68	-2.79	0.35	46.38	-11.72	215.7	63.0	152.7	0.2930	0.51
0.086	20	401.42	-326.78	74.64	10.06	-2.89	0.52	55.18	-11.58	153.5	39.0	114.5	0.2555	0.52
0.086	38	329.26	-253.44	75.82	12.99	-2.96	0.75	65.19	-11.23	111.8	24.7	87.0	0.2236	0.52
0.086	50	302.55	-226.14	76.41	14.59	-2.99	0.89	69.41	-11.08	97.3	20.2	77.1	0.2108	0.53
0.086	100	247.47	-167.10	80.36	19.81	-3.01	1.40	81.79	-10.46	69.2	12.3	56.9	0.1826	0.53
0.086	200	207.99	-123.39	84.59	27.09	-3.03	2.26	95.23	-9.85	49.8	7.8	42.0	0.1641	0.56
-0.082	5	215.16	-242.28	-27.12	2.33	-1.16	-0.09	14.94	-5.16	300.8	90.8	210.0	0.3023	0.48
-0.082	10	167.48	-194.68	-27.20	2.93	-1.23	-0.12	17.03	-5.16	215.1	56.0	159.1	0.2611	0.47
-0.082	20	125.45	-152.16	-26.71	3.67	-1.28	-0.16	19.12	-5.14	152.5	33.4	119.1	0.2202	0.45
-0.082	38	92.71	-119.09	-26.38	4.47	-1.33	-0.22	20.71	-5.04	110.3	20.1	90.1	0.1844	0.44
-0.082	50	80.61	-106.68	-26.07	4.86	-1.34	-0.25	21.12	-4.98	95.8	16.1	79.7	0.1701	0.43
-0.082	100	54.96	-80.54	-25.58	5.92	-1.39	-0.34	20.95	-4.83	66.7	8.9	57.7	0.1374	0.39
-0.082	200	36.81	-61.11	-24.30	6.99	-1.45	-0.43	19.42	-4.66	46.9	5.0	41.8	0.1121	0.35

**Table 4: Trade statistics of different drift levels.** The table shows the trade statistics of the SMA trading rules dependent on different drift levels of the underlying benchmark. The profit and loss figures are in € with respect to an initial investment of 100€.

$\mu$	SMA	ATH	-PiT	ATL	-PiT	MLS	AWD	ALD	Mean Ret.	Vol.	Skew	Kurt.	MaxDD	Sharpe	VaR(5%)	Exp.Exc.Ret.
0.259	5	937.30	2256	78.90	481	11.32	8.52	2.31	0.0006362	0.0200	-0.1898	17.37	0.8221	0.0372	-0.0416	-0.0002626
0.259	10	967.43	2255	79.90	470	11.80	14.21	2.89	0.0006556	0.0196	-0.1353	14.02	0.7835	0.0381	-0.0405	-0.0002432
0.259	20	1012.63	2251	80.81	465	12.37	24.57	3.59	0.0006749	0.0194	-0.1046	12.45	0.7647	0.0390	-0.0395	-0.0002239
0.259	38	1062.67	2249	81.82	445	12.71	42.06	4.38	0.0006974	0.0191	-0.0869	10.95	0.7339	0.0404	-0.0381	-0.0002014
0.259	50	1088.51	2247	82.08	442	12.81	53.35	4.74	0.0007053	0.0190	-0.0801	10.43	0.7257	0.0409	-0.0375	-0.0001935
0.259	100	1173.18	2248	83.15	418	12.77	100.39	5.79	0.0007389	0.0185	-0.0661	8.38	0.6811	0.0431	-0.0355	-0.0001599
0.259	200	1272.35	2253	84.46	365	11.82	200.92	7.43	0.0007771	0.0179	-0.0493	6.77	0.6303	0.0458	-0.0329	-0.0001217
0.086	5	236.55	1573	65.99	1069	12.49	8.18	2.30	0.0000663	0.0163	-0.3257	18.97	0.9290	0.0081	-0.0355	-0.0001408
0.086	10	237.91	1570	66.48	1073	13.24	13.43	2.89	0.0000672	0.0164	-0.3260	19.72	0.9229	0.0081	-0.0353	-0.0001399
0.086	20	241.77	1556	66.55	1094	14.26	22.67	3.63	0.0000716	0.0163	-0.3138	18.65	0.9195	0.0080	-0.0352	-0.0001355
0.086	38	245.31	1545	66.63	1118	15.20	37.44	4.48	0.0000733	0.0163	-0.2864	16.91	0.9177	0.0078	-0.0352	-0.0001338
0.086	50	247.31	1543	66.57	1131	15.62	46.66	4.92	0.0000714	0.0164	-0.2862	17.04	0.9242	0.0077	-0.0353	-0.0001356
0.086	100	254.60	1535	66.92	1149	16.49	81.86	6.20	0.0000747	0.0165	-0.2995	17.47	0.9188	0.0077	-0.0351	-0.0001324
0.086	200	262.71	1513	67.45	1150	16.86	142.07	7.89	0.0000821	0.0164	-0.2670	15.62	0.8977	0.0075	-0.0346	-0.0001249
-0.082	5	127.30	540	57.86	1676	13.73	7.88	2.29	-0.0002051	0.0106	-0.3311	16.25	0.8842	-0.0181	-0.0249	0.0002600
-0.082	10	127.13	528	58.09	1686	14.90	12.76	2.88	-0.0002020	0.0105	-0.3358	15.84	0.8689	-0.0182	-0.0249	0.0002631
-0.082	20	127.24	525	58.83	1707	16.41	21.13	3.64	-0.0001972	0.0104	-0.3328	15.87	0.8547	-0.0182	-0.0250	0.0002679
-0.082	38	127.26	519	59.63	1732	18.12	34.03	4.54	-0.0001898	0.0101	-0.3523	16.09	0.8253	-0.0183	-0.0249	0.0002753
-0.082	50	127.15	521	60.21	1739	18.90	41.84	5.00	-0.0001876	0.0100	-0.3517	15.58	0.8123	-0.0183	-0.0249	0.0002775
-0.082	100	126.83	530	61.43	1779	20.77	70.14	6.43	-0.0001802	0.0099	-0.3856	17.02	0.7848	-0.0183	-0.0254	0.0002848
-0.082	200	127.21	527	63.68	1818	22.61	112.82	8.17	-0.0001708	0.0095	-0.5188	20.57	0.7402	-0.0184	-0.0257	0.0002943

**Table 5: Key figures of timing for different drift levels based on pathwise estimation.** The table shows the average moments of the pathwise return distribution, risk- and performance figures. The SMA trading rules are dependent on different drift levels of the underlying benchmark on a daily basis. ATH stands for all-time-high, ATL for all-time-low, PiT for point-in-time, MLS for maximum loss sequence, AWD for average win trade duration, ALD for average loss trade duration, and MaxDD for maximum drawdown.

$\mu$	SMA	ATH	-PiT	ATL	-PiT	Mean Ret.	Vol.	Skew	Kurt.	MaxDD	Sharpe	Var(5%)
0.259	5	1482.93	2343	86.60	157	0.0008988	0.0164	-0.04952	3.00	0.4995	0.0547	-0.0264
0.259	10	1482.93	2348	86.60	162	0.0008988	0.0164	-0.04952	3.00	0.4995	0.0547	-0.0264
0.259	20	1482.93	2358	86.60	172	0.0008988	0.0164	-0.04952	3.00	0.4995	0.0547	-0.0264
0.259	38	1482.93	2376	86.60	190	0.0008988	0.0164	-0.04952	3.00	0.4995	0.0547	-0.0264
0.259	50	1482.93	2388	86.60	202	0.0008988	0.0164	-0.04952	3.00	0.4995	0.0547	-0.0264
0.259	100	1482.93	2438	86.60	252	0.0008988	0.0164	-0.04952	3.00	0.4995	0.0547	-0.0264
0.259	200	1482.93	2538	64.38	55	0.0008988	0.0164	-0.04952	3.00	0.4995	0.0547	-0.0264
0.086	5	315.81	1663	68.68	849	0.0002071	0.0164	-0.04956	3.00	0.8272	0.0126	-0.0271
0.086	10	315.81	1668	68.68	854	0.0002071	0.0164	-0.04956	3.00	0.8272	0.0126	-0.0271
0.086	20	315.87	1675	68.68	864	0.0002071	0.0164	-0.04956	3.00	0.8272	0.0126	-0.0271
0.086	38	316.10	1682	68.68	882	0.0002071	0.0164	-0.04956	3.00	0.8272	0.0126	-0.0271
0.086	50	316.10	1694	68.68	894	0.0002071	0.0164	-0.04956	3.00	0.8272	0.0126	-0.0271
0.086	100	316.10	1744	68.68	944	0.0002071	0.0164	-0.04956	3.00	0.8272	0.0126	-0.0271
0.086	200	316.10	1844	62.52	797	0.0002071	0.0164	-0.04956	3.00	0.8272	0.0126	-0.0271
-0.082	5	135.34	464	29.98	2032	-0.0004651	0.0165	-0.04959	3.00	1.6646	-0.0283	-0.0278
-0.082	10	135.36	468	29.98	2037	-0.0004651	0.0165	-0.04959	3.00	1.6646	-0.0283	-0.0278
-0.082	20	136.11	462	29.98	2047	-0.0004651	0.0165	-0.04959	3.00	1.6646	-0.0283	-0.0278
-0.082	38	138.65	436	29.98	2065	-0.0004651	0.0165	-0.04959	3.00	1.6646	-0.0283	-0.0278
-0.082	50	138.65	448	29.98	2077	-0.0004651	0.0165	-0.04959	3.00	1.6646	-0.0283	-0.0278
-0.082	100	138.79	477	29.98	2127	-0.0004651	0.0165	-0.04959	3.00	1.6646	-0.0283	-0.0278
-0.082	200	138.79	577	29.82	2213	-0.0004651	0.0165	-0.04959	3.00	1.6646	-0.0283	-0.0278

**Table 6: Key figures of benchmark for different drift levels based on pathwise estimation.** The table shows the moments of the pathwise return distribution of the buy-and-hold approach. The figures depend on different drift levels of the underlying asset and are estimated on a daily basis. ATH stands for all-time-high, ATL for all-time-low, PiT for point-in-time, and MaxDD for maximum drawdown.

$\mu$	SMA	Timing Distribution							Benchmark Distribution						
		Mean Ret.	Vol.	Skew	Kurt.	VaR(5%)	Sharpe	SD	Exp.Exc.Ret.	Mean Ret.	Vol.	Skew	Kurt.	VaR(5%)	Sharpe
0.259	5	0.1442	0.6041	-4.44	27.06	-0.0006	0.2388	-1	-0.0804	0.2246	0.2612	0.0207	2.98	0.0892	0.8599
0.259	10	0.1523	0.5547	-4.72	32.13	0.0113	0.2745	-1	-0.0723	0.2246	0.2612	0.0207	2.98	0.0892	0.8599
0.259	20	0.1593	0.5168	-4.76	34.70	0.0135	0.3082	-1	-0.0653	0.2246	0.2612	0.0207	2.98	0.0892	0.8599
0.259	38	0.1674	0.4740	-4.77	38.02	0.0206	0.3532	-1	-0.0572	0.2246	0.2612	0.0207	2.98	0.0892	0.8599
0.259	50	0.1693	0.4810	-4.79	37.69	0.0222	0.3519	-1	-0.0554	0.2246	0.2612	0.0207	2.98	0.0892	0.8599
0.259	100	0.1795	0.4437	-4.84	43.84	0.0293	0.4046	-1	-0.0451	0.2246	0.2612	0.0207	2.98	0.0892	0.8599
0.259	200	0.1909	0.4009	-4.26	41.82	0.0378	0.4762	-1	-0.0337	0.2246	0.2612	0.0207	2.98	0.0892	0.8599
0.086	5	-0.0046	0.6620	-4.47	24.45	-0.1308	-0.0069	-1	-0.0563	0.0518	0.2614	0.0207	2.98	-0.0837	0.1980
0.086	10	-0.0023	0.6394	-4.56	25.67	-0.1301	-0.0037	-1	-0.0541	0.0518	0.2614	0.0207	2.98	-0.0837	0.1980
0.086	20	0.0005	0.6196	-4.71	27.85	-0.1240	0.0007	-1	-0.0513	0.0518	0.2614	0.0207	2.98	-0.0837	0.1980
0.086	38	0.0012	0.6138	-4.73	28.23	-0.1266	0.0019	-1	-0.0506	0.0518	0.2614	0.0207	2.98	-0.0837	0.1980
0.086	50	-0.0004	0.6340	-4.72	27.95	-0.1337	-0.0006	-1	-0.0522	0.0518	0.2614	0.0207	2.98	-0.0837	0.1980
0.086	100	-0.0004	0.6447	-4.61	26.70	-0.1325	-0.0006	-1	-0.0521	0.0518	0.2614	0.0207	2.98	-0.0837	0.1980
0.086	200	0.0054	0.5960	-4.81	30.10	-0.1200	0.0090	-1	-0.0464	0.0518	0.2614	0.0207	2.98	-0.0837	0.1980
-0.082	5	-0.0625	0.5013	-6.28	46.42	-0.1602	-0.1247	0	0.0537	-0.1162	0.2615	0.0207	2.98	-0.2518	-0.4444
-0.082	10	-0.0613	0.4881	-6.37	47.65	-0.1557	-0.1257	0	0.0549	-0.1162	0.2615	0.0207	2.98	-0.2518	-0.4444
-0.082	20	-0.0605	0.4905	-6.42	48.36	-0.1518	-0.1233	0	0.0558	-0.1162	0.2615	0.0207	2.98	-0.2518	-0.4444
-0.082	38	-0.0558	0.4378	-7.06	59.72	-0.1443	-0.1275	0	0.0604	-0.1162	0.2615	0.0207	2.98	-0.2518	-0.4444
-0.082	50	-0.0575	0.4771	-6.85	54.90	-0.1416	-0.1205	0	0.0588	-0.1162	0.2615	0.0207	2.98	-0.2518	-0.4444
-0.082	100	-0.0536	0.4323	-7.21	62.44	-0.1421	-0.1240	0	0.0626	-0.1162	0.2615	0.0207	2.98	-0.2518	-0.4444
-0.082	200	-0.0514	0.4341	-7.18	60.53	-0.1377	-0.1185	0	0.0648	-0.1162	0.2615	0.0207	2.98	-0.2518	-0.4444

**Table 7: Key figures of timing and benchmark for different drift levels based on estimation of terminal values.** The table shows the moments of the return distribution of terminal results of timing and the corresponding buy-and-hold approach. The figures are dependent on different drift levels of the underlying asset and are estimated on an annual basis. SD stands for stochastic dominance: in case of first-order dominance of timing (buy-and-hold) the value is 1 (-1); in case of second-order dominance of timing (buy-and-hold) the value is 2 (-2). If no dominance can be detected, the value is 0.

$\varphi$	SMA	Tot.Profit	Tot.Loss	Net Result	Av.Profit	Av.Loss	Av.Trade	Max.Win	Max.Loss	No.Trades	No.Win	No.Loss	Hit Ratio	TIM
0.2	5	907.96	-419.77	488.19	8.50	-2.81	1.92	61.08	-13.36	256.5	104.9	151.7	0.4094	0.51
0.2	10	731.83	-340.14	391.68	10.84	-3.02	2.20	70.89	-13.49	180.6	66.0	114.6	0.3665	0.51
0.2	20	582.47	-267.65	314.82	13.93	-3.16	2.54	82.80	-13.43	127.1	40.6	86.5	0.3216	0.51
0.2	38	469.31	-210.27	259.04	17.77	-3.26	2.96	95.90	-13.11	92.0	25.7	66.3	0.2822	0.52
0.2	50	428.41	-188.52	239.89	19.75	-3.29	3.19	101.26	-12.92	80.0	21.1	58.9	0.2669	0.52
0.2	100	344.50	-140.75	203.75	26.45	-3.31	4.02	117.18	-12.04	56.8	12.8	44.0	0.2303	0.52
0.2	200	285.46	-105.41	180.05	35.57	-3.33	5.34	133.85	-11.20	41.2	8.1	33.1	0.2050	0.54
0.025	5	631.79	-513.69	118.10	6.18	-2.67	0.41	41.08	-11.95	295.2	100.4	194.8	0.3408	0.51
0.025	10	517.94	-410.07	107.87	7.99	-2.82	0.53	48.69	-11.90	211.0	63.5	147.5	0.3017	0.51
0.025	20	419.70	-318.52	101.18	10.44	-2.92	0.71	57.86	-11.76	149.9	39.2	110.7	0.2631	0.52
0.025	38	343.44	-247.42	96.01	13.46	-2.99	0.96	68.18	-11.42	109.1	24.9	84.3	0.2303	0.52
0.025	50	315.27	-220.77	94.50	15.10	-3.02	1.11	72.49	-11.26	95.0	20.4	74.6	0.2173	0.52
0.025	100	257.22	-163.40	93.81	20.47	-3.04	1.65	85.24	-10.62	67.5	12.3	55.2	0.1879	0.53
0.025	200	215.77	-120.87	94.90	27.96	-3.06	2.55	99.01	-10.00	48.6	7.8	40.8	0.1687	0.55
-0.1	5	491.74	-593.99	-102.26	5.05	-2.60	-0.31	32.08	-11.21	326.3	95.8	230.5	0.2940	0.51
-0.1	10	410.06	-471.41	-61.35	6.59	-2.73	-0.25	38.50	-11.11	235.7	61.0	174.7	0.2596	0.52
-0.1	20	337.77	-364.07	-26.30	8.70	-2.82	-0.13	46.24	-10.95	168.6	38.0	130.7	0.2265	0.52
-0.1	38	280.31	-280.86	-0.55	11.35	-2.88	0.05	55.12	-10.66	123.1	24.1	99.0	0.1982	0.53
-0.1	50	258.74	-249.83	8.91	12.78	-2.90	0.16	58.91	-10.49	107.3	19.8	87.5	0.1870	0.53
-0.1	100	213.72	-183.98	29.74	17.56	-2.92	0.57	70.09	-9.96	76.3	12.0	64.3	0.1617	0.54
-0.1	200	181.18	-134.84	46.34	24.17	-2.95	1.29	82.42	-9.34	54.8	7.6	47.2	0.1466	0.56

**Table 8: Trade statistics of different autocorrelation levels.** The table shows the trade statistics of the SMA trading rules dependent on different first-lag autocorrelation levels of the underlying benchmark. The profit and loss figures are in € with respect to an initial investment of 100 €.

$\varphi$	SMA	ATH	-PiT	ATL	-PiT	MLS	AWD	ALD	Mean Ret.	Vol.	Skew	Kurt.	MaxDD	Sharpe	VaR(5%)	Exp.Exc.Ret.
0.2	5	609.58	2371	94.48	69	9.48	8.66	2.43	0.0006207	0.0074	0.2694	9.16	0.1854	0.0817	-0.0156	0.0004148
0.2	10	520.62	2279	92.98	113	10.06	13.98	3.14	0.0005457	0.0083	0.1669	8.41	0.2332	0.0640	-0.0178	0.0003398
0.2	20	453.79	2152	91.31	193	10.80	23.20	4.02	0.0004711	0.0092	0.0935	7.83	0.2961	0.0493	-0.0203	0.0002652
0.2	38	409.19	2007	89.15	316	11.61	37.73	5.03	0.0004061	0.0102	0.0406	7.47	0.3664	0.0384	-0.0225	0.0002003
0.2	50	395.22	1945	88.03	378	11.99	46.59	5.54	0.0003801	0.0106	0.0217	7.43	0.3993	0.0345	-0.0235	0.0001742
0.2	100	373.23	1806	84.80	571	12.87	80.41	7.06	0.0003214	0.0116	-0.0219	7.40	0.4896	0.0265	-0.0258	0.0001155
0.2	200	363.20	1673	81.03	734	13.27	137.26	9.00	0.0002739	0.0126	-0.0559	7.41	0.5756	0.0205	-0.0277	0.0000681
0.025	5	271.24	1771	77.10	730	12.06	8.23	2.32	0.0002065	0.0132	-0.0924	10.37	0.6387	0.0177	-0.0295	-0.0000006
0.025	10	264.81	1720	75.09	808	12.80	13.48	2.92	0.0001812	0.0138	-0.1154	11.37	0.6871	0.0153	-0.0307	-0.0000259
0.025	20	262.40	1659	73.21	888	13.80	22.72	3.67	0.0001589	0.0144	-0.1359	11.89	0.7353	0.0133	-0.0318	-0.0000482
0.025	38	261.58	1623	71.81	978	14.72	37.45	4.54	0.0001399	0.0148	-0.1698	12.28	0.7752	0.0117	-0.0325	-0.0000673
0.025	50	262.13	1610	71.16	1006	15.13	46.61	5.00	0.0001310	0.0151	-0.1833	13.04	0.7997	0.0111	-0.0329	-0.0000762
0.025	100	266.58	1577	70.14	1065	16.01	81.67	6.29	0.0001157	0.0155	-0.2305	14.23	0.8343	0.0100	-0.0335	-0.0000915
0.025	200	272.87	1537	69.66	1092	16.34	141.53	8.02	0.0001111	0.0157	-0.2308	13.63	0.8395	0.0091	-0.0335	-0.0000961
-0.1	5	143.53	673	-34.34	2197	14.34	7.99	2.23	-0.0012504	0.0485	-5.7505	250.49	3.9456	-0.0257	-0.0837	-0.0014573
-0.1	10	158.46	868	-2.17	2048	15.24	13.21	2.78	-0.0008848	0.0399	-3.8468	167.52	3.1302	-0.0195	-0.0707	-0.0010917
-0.1	20	175.89	1060	21.22	1851	16.26	22.45	3.45	-0.0005732	0.0328	-2.4058	110.95	2.4333	-0.0128	-0.0597	-0.0007802
-0.1	38	191.10	1193	36.37	1680	17.30	37.41	4.24	-0.0003501	0.0272	-1.5051	71.95	1.9101	-0.0074	-0.0517	-0.0005570
-0.1	50	197.48	1244	40.98	1611	17.74	46.77	4.65	-0.0002907	0.0253	-1.3987	63.99	1.7521	-0.0057	-0.0490	-0.0004976
-0.1	100	213.10	1340	50.07	1484	18.79	82.85	5.83	-0.0001545	0.0220	-0.9166	42.40	1.4253	-0.0018	-0.0439	-0.0003614
-0.1	200	227.44	1381	56.56	1387	19.02	145.02	7.39	-0.0000675	0.0201	-0.6284	31.14	1.2240	0.0010	-0.0404	-0.0002744

**Table 9: Key figures of timing for different autocorrelation levels based on pathwise estimation.** The table shows the moments of

the pathwise return distribution, risk- and performance figures of the SMA trading rules. The figures depend on different first-lag autocorrelation levels of the underlying benchmark and are estimated on a daily basis. ATH stands for all-time-high, ATL for all-time-low, PiT for point-in-time, MLS for maximum loss sequence, AWD for average win trade duration, ALD for average loss trade duration, and MaxDD for maximum drawdown.

$\varphi$	SMA	ATH	-PiT	ATL	-PiT	Mean Ret.	Vol.	Skew	Kurt.	MaxDD	Sharpe	Var(5%)
0.2	5	397.14	1587	62.13	925	0.0002059	0.0165	-0.04939	3.00	1.0458	0.0125	-0.0272
0.2	10	397.14	1592	62.13	930	0.0002059	0.0165	-0.04939	3.00	1.0458	0.0125	-0.0272
0.2	20	397.24	1597	62.13	940	0.0002059	0.0165	-0.04939	3.00	1.0458	0.0125	-0.0272
0.2	38	397.59	1601	62.13	958	0.0002059	0.0165	-0.04939	3.00	1.0458	0.0125	-0.0272
0.2	50	397.59	1613	62.13	970	0.0002059	0.0165	-0.04939	3.00	1.0458	0.0125	-0.0272
0.2	100	397.59	1663	62.13	1020	0.0002059	0.0165	-0.04939	3.00	1.0458	0.0125	-0.0272
0.2	200	397.59	1763	56.05	897	0.0002059	0.0165	-0.04939	3.00	1.0458	0.0125	-0.0272
0.025	5	323.80	1653	67.90	859	0.0002072	0.0164	-0.04953	3.00	0.8516	0.0126	-0.0271
0.025	10	323.80	1658	67.90	864	0.0002072	0.0164	-0.04953	3.00	0.8516	0.0126	-0.0271
0.025	20	323.87	1665	67.90	874	0.0002072	0.0164	-0.04953	3.00	0.8516	0.0126	-0.0271
0.025	38	324.11	1672	67.90	892	0.0002072	0.0164	-0.04953	3.00	0.8516	0.0126	-0.0271
0.025	50	324.11	1684	67.90	904	0.0002072	0.0164	-0.04953	3.00	0.8516	0.0126	-0.0271
0.025	100	324.11	1734	67.90	954	0.0002072	0.0164	-0.04953	3.00	0.8516	0.0126	-0.0271
0.025	200	324.11	1834	61.76	808	0.0002072	0.0164	-0.04953	3.00	0.8516	0.0126	-0.0271
-0.1	5	288.84	1697	71.66	811	0.0002069	0.0165	-0.04979	3.00	0.7375	0.0126	-0.0272
-0.1	10	288.84	1702	71.66	816	0.0002069	0.0165	-0.04979	3.00	0.7375	0.0126	-0.0272
-0.1	20	288.89	1709	71.66	826	0.0002069	0.0165	-0.04979	3.00	0.7375	0.0126	-0.0272
-0.1	38	289.08	1719	71.66	844	0.0002069	0.0165	-0.04979	3.00	0.7375	0.0126	-0.0272
-0.1	50	289.08	1731	71.66	856	0.0002069	0.0165	-0.04979	3.00	0.7375	0.0126	-0.0272
-0.1	100	289.08	1781	71.66	906	0.0002069	0.0165	-0.04979	3.00	0.7375	0.0126	-0.0272
-0.1	200	289.08	1881	65.42	745	0.0002069	0.0165	-0.04979	3.00	0.7375	0.0126	-0.0272

**Table 10: Key figures of benchmark for different autocorrelation levels based on pairwise estimation.** The table shows the average moments of the pathwise return distribution of the buy-and-hold approach. The figures depend on different first-lag autocorrelation levels of the underlying asset and are estimate on a daily basis. ATH stands for all-time-high, ATL for all-time-low, PiT for point-in-time, and MaxDD for maximum drawdown.

$\varphi$	SMA	Timing Distribution										Benchmark Distribution					
		Mean Ret.	Vol.	Skew	Kurt.	VaR(5%)	Sharpe	SD	Exp. Exc. Ret.	Mean Ret.	Vol.	Skew	Kurt.	VaR(5%)	Sharpe		
0.2	5	0.1551	0.1993	0.51	3.22	0.0610	0.7785	0	0.1038	0.0514	0.3210	0.0203	2.98	-0.1150	0.1603		
0.2	10	0.1364	0.2023	0.53	3.26	0.0424	0.6742	0	0.0850	0.0514	0.3210	0.0203	2.98	-0.1150	0.1603		
0.2	20	0.1177	0.2081	0.57	3.31	0.0226	0.5658	0	0.0663	0.0514	0.3210	0.0203	2.98	-0.1150	0.1603		
0.2	38	0.1015	0.2149	0.57	3.34	0.0037	0.4722	0	0.0501	0.0514	0.3210	0.0203	2.98	-0.1150	0.1603		
0.2	50	0.0948	0.2274	-0.72	22.76	-0.0044	0.4169	0	0.0434	0.0514	0.3210	0.0203	2.98	-0.1150	0.1603		
0.2	100	0.0799	0.2501	-1.79	36.88	-0.0228	0.3194	0	0.0285	0.0514	0.3210	0.0203	2.98	-0.1150	0.1603		
0.2	200	0.0679	0.2681	-1.98	36.19	-0.0385	0.2533	0	0.0166	0.0514	0.3210	0.0203	2.98	-0.1150	0.1603		
0.025	5	0.0465	0.3816	-6.55	65.38	-0.0531	0.1219	0	-0.0045	0.0518	0.2681	0.0206	2.98	-0.0872	0.1931		
0.025	10	0.0385	0.4206	-6.26	56.01	-0.0641	0.0915	0	-0.0123	0.0518	0.2681	0.0206	2.98	-0.0872	0.1931		
0.025	20	0.0322	0.4393	-5.92	50.29	-0.0737	0.0734	0	-0.0185	0.0518	0.2681	0.0206	2.98	-0.0872	0.1931		
0.025	38	0.0263	0.4718	-5.74	45.82	-0.0848	0.0557	0	-0.0242	0.0518	0.2681	0.0206	2.98	-0.0872	0.1931		
0.025	50	0.0227	0.5001	-5.60	42.67	-0.0935	0.0454	0	-0.0273	0.0518	0.2681	0.0206	2.98	-0.0872	0.1931		
0.025	100	0.0158	0.5574	-5.15	34.87	-0.1043	0.0284	0	-0.0338	0.0518	0.2681	0.0206	2.98	-0.0872	0.1931		
0.025	200	0.0157	0.5477	-5.17	35.74	-0.1026	0.0286	-1	-0.0338	0.0518	0.2681	0.0206	2.98	-0.0872	0.1931		
-0.1	5	-0.7154	1.4721	0.60	1.69	-1.2249	-0.4860	-1	-0.7242	0.0517	0.2367	0.0208	2.98	-0.0709	0.2185		
-0.1	10	-0.5057	1.6219	-0.25	1.29	-1.2220	-0.3118	-1	-0.5208	0.0517	0.2367	0.0208	2.98	-0.0709	0.2185		
-0.1	20	-0.3278	1.5259	-0.96	2.16	-1.1906	-0.2148	-1	-0.3527	0.0517	0.2367	0.0208	2.98	-0.0709	0.2185		
-0.1	38	-0.2032	1.3222	-1.64	4.04	-1.1438	-0.1536	-1	-0.2374	0.0517	0.2367	0.0208	2.98	-0.0709	0.2185		
-0.1	50	-0.1698	1.2488	-1.88	4.96	-1.1216	-0.1360	-1	-0.2067	0.0517	0.2367	0.0208	2.98	-0.0709	0.2185		
-0.1	100	-0.1011	1.0506	-2.56	8.38	-1.0640	-0.0963	-1	-0.1431	0.0517	0.2367	0.0208	2.98	-0.0709	0.2185		
-0.1	200	-0.0559	0.8761	-3.28	13.41	-0.9713	-0.0638	-1	-0.1010	0.0517	0.2367	0.0208	2.98	-0.0709	0.2185		

**Table 11: Key figures of timing and benchmark for different autocorrelation levels based on estimation of terminal values.**

The table shows the moments of the return distribution of terminal results of timing and the corresponding buy-and-hold approach. The figures depend on different first-lag autocorrelation levels of the underlying asset and are estimated on an annual basis. SD stands for stochastic dominance: in case of first-order dominance of timing (buy-and-hold) the value is 1 (-1); in case of second-order dominance of timing (buy-and-hold) the value is 2 (-2). If no dominance can be detected, the value is 0.

$\sigma$	SMA	Tot.Profit	Tot.Loss	Net Result	Av.Profit	Av.Loss	Av.Trade	Max.Win	Max.Loss	No.Trades	No.Win	No.Loss	Hit Ratio	TIM
0.39	5	1130.35	-995.49	134.86	11.12	-5.00	0.46	86.10	-27.37	301.2	98.8	202.4	0.3286	0.51
0.39	10	928.60	-793.09	135.51	14.38	-5.27	0.66	101.31	-27.07	215.7	62.4	153.3	0.2901	0.51
0.39	20	754.43	-614.55	139.88	18.80	-5.46	0.98	119.01	-26.56	153.6	38.5	115.1	0.2523	0.51
0.39	38	618.04	-476.03	142.02	24.19	-5.58	1.41	138.34	-25.51	111.9	24.3	87.6	0.2199	0.51
0.39	50	567.49	-423.97	143.52	27.24	-5.62	1.67	145.85	-24.84	97.5	19.9	77.6	0.2067	0.51
0.39	100	463.28	-312.00	151.29	36.87	-5.62	2.62	167.72	-23.00	69.6	12.0	57.5	0.1775	0.52
0.39	200	387.92	-228.89	159.03	50.47	-5.62	4.25	189.98	-20.92	50.2	7.6	42.6	0.1583	0.53
0.26	5	600.61	-528.46	72.15	5.92	-2.65	0.25	38.99	-11.78	301.1	99.6	201.5	0.3313	0.51
0.26	10	493.86	-421.35	72.51	7.68	-2.79	0.35	46.38	-11.72	215.7	63.0	152.7	0.2930	0.51
0.26	20	401.42	-326.78	74.64	10.06	-2.89	0.52	55.18	-11.58	153.5	39.0	114.5	0.2555	0.52
0.26	38	329.26	-253.44	75.82	12.99	-2.96	0.75	65.19	-11.23	111.8	24.7	87.0	0.2236	0.52
0.26	50	302.55	-226.14	76.41	14.59	-2.99	0.89	69.41	-11.08	97.3	20.2	77.1	0.2108	0.53
0.26	100	247.47	-167.10	80.36	19.81	-3.01	1.40	81.79	-10.46	69.2	12.3	56.9	0.1826	0.53
0.26	200	207.99	-123.39	84.59	27.09	-3.03	2.26	95.23	-9.85	49.8	7.8	42.0	0.1641	0.56
0.16	5	331.04	-285.03	46.00	3.25	-1.43	0.16	19.31	-5.51	301.1	100.9	200.1	0.3357	0.52
0.16	10	273.68	-227.14	46.54	4.22	-1.51	0.22	23.20	-5.51	215.5	64.1	151.4	0.2983	0.52
0.16	20	223.89	-176.12	47.77	5.56	-1.57	0.33	28.07	-5.47	153.3	39.8	113.5	0.2613	0.53
0.16	38	185.30	-136.52	48.78	7.25	-1.60	0.48	33.72	-5.37	111.4	25.3	86.1	0.2299	0.54
0.16	50	171.08	-121.52	49.57	8.15	-1.62	0.57	36.23	-5.30	96.9	20.8	76.1	0.2181	0.54
0.16	100	141.60	-89.91	51.69	11.24	-1.63	0.89	43.92	-5.07	68.7	12.7	56.0	0.1898	0.56
0.16	200	121.08	-66.28	54.80	15.66	-1.66	1.46	52.80	-4.90	49.0	8.1	41.0	0.1731	0.59

**Table 12: Trade statistics of different volatility levels.** The table shows the trade statistics of the SMA trading rules. The figures depend on different volatility levels of the underlying benchmark. The profit and loss figures are in € with respect to an initial investment of 100€.

$\sigma$	SMA	ATH	-PiT	ATL	-PiT	MLS	AWD	ALD	Mean Ret.	Vol.	Skew	Kurt.	MaxDD	Sharpe	VaR(5%)	Exp.Exc.Ret.
0.39	5	379.07	1460	38.80	1188	12.58	8.14	2.30	-0.0000924	0.0285	-1.3474	63.95	1.7440	0.0027	-0.0594	-0.0002895
0.39	10	381.99	1465	39.88	1188	13.38	13.32	2.89	-0.0000837	0.0284	-1.3159	60.90	1.7213	0.0027	-0.0593	-0.0002809
0.39	20	390.46	1443	40.32	1209	14.43	22.39	3.62	-0.0000848	0.0286	-1.3051	60.79	1.7382	0.0026	-0.0593	-0.0002819
0.39	38	399.02	1428	40.87	1240	15.49	36.77	4.47	-0.0000938	0.0287	-1.3177	62.10	1.7596	0.0022	-0.0593	-0.0002909
0.39	50	403.16	1427	41.07	1256	15.94	45.74	4.92	-0.0000934	0.0287	-1.3259	61.65	1.7524	0.0021	-0.0594	-0.0002905
0.39	100	419.09	1419	42.06	1281	16.98	79.47	6.19	-0.0000891	0.0288	-1.3233	60.89	1.7480	0.0020	-0.0593	-0.0002862
0.39	200	436.46	1388	44.09	1300	17.38	136.47	7.89	-0.0000786	0.0286	-1.2092	55.57	1.7247	0.0018	-0.0587	-0.0002758
0.26	5	236.55	1573	65.99	1069	12.49	8.18	2.30	0.0000663	0.0163	-0.3257	18.97	0.9290	0.0081	-0.0355	-0.0001408
0.26	10	237.91	1570	66.48	1073	13.24	13.43	2.89	0.0000672	0.0164	-0.3260	19.72	0.9229	0.0081	-0.0353	-0.0001399
0.26	20	241.77	1556	66.55	1094	14.26	22.67	3.63	0.0000716	0.0163	-0.3138	18.65	0.9195	0.0080	-0.0352	-0.0001355
0.26	38	245.31	1545	66.63	1118	15.20	37.44	4.48	0.0000733	0.0163	-0.2864	16.91	0.9177	0.0078	-0.0352	-0.0001338
0.26	50	247.31	1543	66.57	1131	15.62	46.66	4.92	0.0000714	0.0164	-0.2862	17.04	0.9242	0.0077	-0.0353	-0.0001356
0.26	100	254.60	1535	66.92	1149	16.49	81.86	6.20	0.0000747	0.0165	-0.2995	17.47	0.9188	0.0077	-0.0351	-0.0001324
0.26	200	262.71	1513	67.45	1150	16.86	142.07	7.89	0.0000821	0.0164	-0.2670	15.62	0.8977	0.0075	-0.0346	-0.0001249
0.16	5	174.91	1730	82.05	907	12.29	8.23	2.31	0.0001116	0.0086	-0.0124	6.54	0.4263	0.0138	-0.0194	-0.0000873
0.16	10	175.83	1726	82.23	894	12.99	13.56	2.90	0.0001130	0.0086	-0.0151	6.49	0.4235	0.0138	-0.0194	-0.0000859
0.16	20	177.83	1714	82.25	917	13.91	23.02	3.63	0.0001151	0.0086	-0.0158	6.31	0.4244	0.0138	-0.0193	-0.0000838
0.16	38	179.93	1703	82.29	929	14.82	38.31	4.48	0.0001169	0.0087	-0.0170	6.12	0.4249	0.0137	-0.0193	-0.0000821
0.16	50	181.16	1693	82.29	936	15.17	47.83	4.91	0.0001178	0.0087	-0.0187	6.10	0.4265	0.0137	-0.0193	-0.0000812
0.16	100	184.96	1690	82.32	953	15.92	85.16	6.17	0.0001207	0.0088	-0.0248	5.97	0.4278	0.0137	-0.0192	-0.0000783
0.16	200	189.69	1669	82.40	944	16.15	150.85	7.80	0.0001260	0.0089	-0.0272	5.63	0.4287	0.0137	-0.0190	-0.0000729

**Table 13: Key figures of timing for different volatility levels based on pathwise estimation.** The table shows the moments of the pathwise return distribution, risk- and performance figures of the SMA trading rules. The figures depend on different volatility levels of the underlying benchmark and are estimated on a daily basis. ATH stands for all-time-high, ATL for all-time-low, PiT for point-in-time, MLS for maximum loss sequence, AWD for average win trade duration, ALD for average loss trade duration, and MaxDD for maximum drawdown.

$\sigma$	SMA	ATH	-PiT	ATL	-PiT	Mean Ret.	Vol.	Skew	Kurt.	MaxDD	Sharpe	VarR(5%)
0.39	5	535.75	1519	54.70	994	0.0001971	0.0247	-0.07427	3.01	1.3334	0.0080	-0.0410
0.39	10	535.75	1524	54.70	999	0.0001971	0.0247	-0.07427	3.01	1.3334	0.0080	-0.0410
0.39	20	535.88	1530	54.70	1009	0.0001971	0.0247	-0.07427	3.01	1.3334	0.0080	-0.0410
0.39	38	536.37	1534	54.70	1027	0.0001971	0.0247	-0.07427	3.01	1.3334	0.0080	-0.0410
0.39	50	536.37	1546	54.70	1039	0.0001971	0.0247	-0.07427	3.01	1.3334	0.0080	-0.0410
0.39	100	536.37	1596	54.70	1089	0.0001971	0.0247	-0.07427	3.01	1.3334	0.0080	-0.0410
0.39	200	536.37	1696	47.35	945	0.0001971	0.0247	-0.07427	3.01	1.3334	0.0080	-0.0410
0.26	5	315.81	1663	68.68	849	0.0002071	0.0164	-0.04956	3.00	0.8272	0.0126	-0.0271
0.26	10	315.81	1668	68.68	854	0.0002071	0.0164	-0.04956	3.00	0.8272	0.0126	-0.0271
0.26	20	315.87	1675	68.68	864	0.0002071	0.0164	-0.04956	3.00	0.8272	0.0126	-0.0271
0.26	38	316.10	1682	68.68	882	0.0002071	0.0164	-0.04956	3.00	0.8272	0.0126	-0.0271
0.26	50	316.10	1694	68.68	894	0.0002071	0.0164	-0.04956	3.00	0.8272	0.0126	-0.0271
0.26	100	316.10	1744	68.68	944	0.0002071	0.0164	-0.04956	3.00	0.8272	0.0126	-0.0271
0.26	200	316.10	1844	62.52	797	0.0002071	0.0164	-0.04956	3.00	0.8272	0.0126	-0.0271
0.16	5	220.85	1857	82.06	654	0.0001989	0.0101	-0.03060	3.00	0.4588	0.0197	-0.0166
0.16	10	220.85	1862	82.06	659	0.0001989	0.0101	-0.03060	3.00	0.4588	0.0197	-0.0166
0.16	20	220.87	1869	82.06	669	0.0001989	0.0101	-0.03060	3.00	0.4588	0.0197	-0.0166
0.16	38	220.94	1881	82.06	687	0.0001989	0.0101	-0.03060	3.00	0.4588	0.0197	-0.0166
0.16	50	220.94	1893	82.06	699	0.0001989	0.0101	-0.03060	3.00	0.4588	0.0197	-0.0166
0.16	100	220.94	1943	82.06	749	0.0001989	0.0101	-0.03060	3.00	0.4588	0.0197	-0.0166
0.16	200	220.94	2043	76.82	580	0.0001989	0.0101	-0.03060	3.00	0.4588	0.0197	-0.0166

**Table 14: Key figures of benchmark for different volatility levels based on pathwise estimation.** The table shows the moments of the pathwise return distribution of the buy-and-hold approach. The figures depend on different volatility levels of the underlying asset and are estimated on a daily basis. ATH stands for all-time-high, ATL for all-time-low, PiT for point-in-time, and MaxDD for maximum drawdown.

		Timing Distribution										Benchmark Distribution									
$\sigma$	SMA	Mean Ret.	Vol.	Skew	Kurt.	VaR(5%)	Sharpe	SD	Exp.Exc.Ret.	Mean Ret.	Vol.	Skew	Kurt.	VaR(5%)	Sharpe						
0.39	5	-0.1261	1.2656	-1.70	4.45	-1.0641	-0.0996	-1	-0.1659	0.0493	0.3922	0.0202	2.98	-0.1540	0.1256						
0.39	10	-0.1181	1.2388	-1.77	4.76	-1.0530	-0.0954	-1	-0.1586	0.0493	0.3922	0.0202	2.98	-0.1540	0.1256						
0.39	20	-0.1167	1.2396	-1.79	4.82	-1.0600	-0.0941	-1	-0.1567	0.0493	0.3922	0.0202	2.98	-0.1540	0.1256						
0.39	38	-0.1230	1.2631	-1.73	4.61	-1.0637	-0.0974	-1	-0.1627	0.0493	0.3922	0.0202	2.98	-0.1540	0.1256						
0.39	50	-0.1233	1.2628	-1.73	4.58	-1.0594	-0.0976	-1	-0.1629	0.0493	0.3922	0.0202	2.98	-0.1540	0.1256						
0.39	100	-0.1189	1.2556	-1.76	4.75	-1.0594	-0.0947	-1	-0.1583	0.0493	0.3922	0.0202	2.98	-0.1540	0.1256						
0.39	200	-0.1089	1.2214	-1.84	5.14	-1.0526	-0.0892	-1	-0.1490	0.0493	0.3922	0.0202	2.98	-0.1540	0.1256						
0.26	5	-0.0046	0.6620	-4.47	24.45	-0.1308	-0.0069	-1	-0.0532	0.0518	0.2614	0.0207	2.98	-0.0837	0.1980						
0.26	10	-0.0023	0.6394	-4.56	25.67	-0.1301	-0.0037	-1	-0.0513	0.0518	0.2614	0.0207	2.98	-0.0837	0.1980						
0.26	20	0.0005	0.6196	-4.71	27.85	-0.1240	0.0007	-1	-0.0486	0.0518	0.2614	0.0207	2.98	-0.0837	0.1980						
0.26	38	0.0012	0.6138	-4.73	28.23	-0.1266	0.0019	-1	-0.0480	0.0518	0.2614	0.0207	2.98	-0.0837	0.1980						
0.26	50	-0.0004	0.6340	-4.72	27.95	-0.1337	-0.0006	-1	-0.0489	0.0518	0.2614	0.0207	2.98	-0.0837	0.1980						
0.26	100	-0.0004	0.6447	-4.61	26.70	-0.1325	-0.0006	-1	-0.0490	0.0518	0.2614	0.0207	2.98	-0.0837	0.1980						
0.26	200	0.0054	0.5960	-4.81	30.10	-0.1200	0.0090	-1	-0.0437	0.0518	0.2614	0.0207	2.98	-0.0837	0.1980						
0.16	5	0.0276	0.1606	-6.52	184.51	-0.0436	0.1720	-1	-0.0220	0.0497	0.1608	0.0210	2.98	-0.0337	0.3091						
0.16	10	0.0280	0.1581	-4.84	112.00	-0.0433	0.1771	-1	-0.0217	0.0497	0.1608	0.0210	2.98	-0.0337	0.3091						
0.16	20	0.0285	0.1586	-4.74	118.88	-0.0432	0.1800	-1	-0.0211	0.0497	0.1608	0.0210	2.98	-0.0337	0.3091						
0.16	38	0.0291	0.1493	-1.52	39.06	-0.0424	0.1952	-1	-0.0206	0.0497	0.1608	0.0210	2.98	-0.0337	0.3091						
0.16	50	0.0293	0.1581	-3.82	103.84	-0.0437	0.1853	-1	-0.0204	0.0497	0.1608	0.0210	2.98	-0.0337	0.3091						
0.16	100	0.0299	0.1681	-5.43	150.12	-0.0445	0.1780	-1	-0.0197	0.0497	0.1608	0.0210	2.98	-0.0337	0.3091						
0.16	200	0.0314	0.1593	-1.29	34.88	-0.0450	0.1973	-1	-0.0183	0.0497	0.1608	0.0210	2.98	-0.0337	0.3091						

**Table 15: Key figures of timing and benchmark for different volatility levels based on estimation of terminal values.** The table shows the moments of the return distribution of terminal results of timing and the corresponding buy-and-hold approach. The figures depend on different volatility levels of the underlying asset and are estimated on an annual basis. SD stands for stochastic dominance: in case of first-order dominance of timing (buy-and-hold) the value is 1 (-1); in case of second-order dominance of timing (buy-and-hold) the value is 2 (-2). If no dominance can be detected, the value is 0.

$\sigma$	SMA	Tot.Profit	Tot.Loss	Net Result	Av.Profit	Av.Loss	Av.Trade	Max.Win	Max.Loss	No.Trades	No.Win	No.Loss	Hit Ratio	TiM
0.39	5	744.73	-644.01	100.72	7.19	-3.20	0.34	61.63	-20.75	305.6	101.6	203.9	0.3331	0.51
0.39	10	615.18	-513.35	101.83	9.32	-3.37	0.48	70.53	-20.43	219.2	64.4	154.7	0.2949	0.52
0.39	20	504.20	-399.27	104.94	12.32	-3.51	0.72	81.45	-19.82	155.6	39.9	115.7	0.2577	0.53
0.39	38	417.46	-310.41	107.04	16.06	-3.62	1.04	92.85	-18.84	112.7	25.2	87.4	0.2265	0.53
0.39	50	385.94	-277.85	108.08	18.11	-3.67	1.23	97.85	-18.46	97.9	20.7	77.3	0.2142	0.54
0.39	100	321.27	-206.67	114.60	25.17	-3.78	1.99	113.19	-17.08	68.7	12.5	56.2	0.1867	0.55
0.39	200	274.50	-153.21	121.29	35.70	-3.84	3.23	131.06	-15.63	49.3	7.8	41.5	0.1657	0.56
0.26	5	435.73	-374.72	61.01	4.20	-1.86	0.21	32.72	-10.77	305.6	102.4	203.2	0.3357	0.52
0.26	10	360.62	-299.03	61.59	5.46	-1.96	0.29	37.68	-10.68	219.1	65.1	154.0	0.2979	0.52
0.26	20	295.79	-232.65	63.14	7.23	-2.04	0.43	43.81	-10.33	155.5	40.3	115.2	0.2609	0.53
0.26	38	245.62	-181.11	64.52	9.45	-2.11	0.63	50.41	-9.88	112.6	25.6	86.9	0.2300	0.54
0.26	50	227.44	-161.92	65.52	10.68	-2.14	0.75	53.66	-9.72	97.8	21.0	76.8	0.2178	0.55
0.26	100	189.67	-120.80	68.87	14.89	-2.21	1.20	62.78	-9.10	68.4	12.7	55.7	0.1911	0.56
0.26	200	162.99	-90.24	72.75	21.14	-2.27	1.95	74.23	-8.55	48.9	8.0	41.0	0.1711	0.59
0.16	5	305.60	-256.57	49.03	2.92	-1.28	0.16	21.78	-7.03	305.5	103.7	201.7	0.3401	0.52
0.16	10	254.38	-204.60	49.78	3.81	-1.35	0.24	25.24	-6.97	218.8	66.1	152.7	0.3030	0.53
0.16	20	210.08	-159.02	51.06	5.07	-1.41	0.35	29.57	-6.75	155.1	41.1	114.0	0.2667	0.54
0.16	38	176.02	-123.48	52.54	6.69	-1.45	0.51	34.38	-6.48	111.9	26.2	85.8	0.2363	0.56
0.16	50	163.65	-110.26	53.39	7.57	-1.47	0.60	36.85	-6.36	97.1	21.5	75.7	0.2245	0.56
0.16	100	138.16	-82.12	56.04	10.75	-1.53	0.98	44.01	-6.03	67.4	13.0	54.4	0.1983	0.58
0.16	200	120.55	-61.16	59.39	15.69	-1.57	1.60	53.37	-5.68	47.9	8.1	39.8	0.1776	0.61

**Table 16: Trade statistics of underlying with clustered volatilities.** The table shows the trade statistics of the SMA trading rules if volatility clustering is applied in the underlying benchmark. The profit and loss figures are in € with respect to an initial investment of 100€.

$\sigma$	SMA	ATH	-PiT	ATL	-PiT	MLS	AWD	ALD	Mean Ret.	Vol.	Skew	Kurt.	MaxDD	Sharpe	VaR(5%)	Exp.Exc.Ret.
0.39	5	290.97	1564	57.17	1073	12.43	8.15	2.26	0.0000336	0.0208	-0.9066	45.27	1.2052	0.0071	-0.0422	-0.0001821
0.39	10	293.45	1554	58.09	1077	13.20	13.40	2.82	0.0000371	0.0209	-0.8347	42.89	1.2035	0.0071	-0.0421	-0.0001786
0.39	20	299.36	1546	58.45	1095	14.14	22.74	3.54	0.0000402	0.0209	-0.8292	40.97	1.1972	0.0070	-0.0420	-0.0001755
0.39	38	305.15	1538	59.32	1112	15.04	37.79	4.39	0.0000445	0.0208	-0.8117	39.57	1.1895	0.0070	-0.0418	-0.0001712
0.39	50	307.58	1538	59.67	1114	15.40	47.25	4.82	0.0000479	0.0206	-0.8133	39.09	1.1773	0.0070	-0.0413	-0.0001678
0.39	100	318.57	1528	60.12	1135	16.05	83.08	6.11	0.0000548	0.0206	-0.8230	39.15	1.1618	0.0070	-0.0411	-0.0001609
0.39	200	330.24	1498	60.52	1153	16.64	146.83	7.61	0.0000586	0.0208	-0.8051	37.24	1.1688	0.0068	-0.0412	-0.0001571
0.26	5	206.40	1660	74.35	957	12.33	8.18	2.26	0.0001010	0.0124	-0.2381	17.76	0.6635	0.0112	-0.0262	-0.0001079
0.26	10	207.77	1655	74.73	966	13.07	13.48	2.83	0.0001068	0.0122	-0.2258	16.38	0.6466	0.0112	-0.0259	-0.0001021
0.26	20	210.74	1644	74.76	978	13.98	22.95	3.54	0.0001061	0.0123	-0.2459	16.44	0.6506	0.0111	-0.0258	-0.0001028
0.26	38	213.56	1633	75.24	993	14.76	38.30	4.39	0.0001112	0.0122	-0.2511	16.06	0.6393	0.0111	-0.0255	-0.0000977
0.26	50	215.40	1634	75.42	1005	15.15	47.99	4.81	0.0001118	0.0123	-0.2518	16.10	0.6428	0.0112	-0.0255	-0.0000971
0.26	100	220.75	1626	75.46	1014	15.70	85.67	6.08	0.0001155	0.0123	-0.2598	15.34	0.6375	0.0113	-0.0254	-0.0000935
0.26	200	227.12	1601	75.38	1019	16.11	151.82	7.60	0.0001195	0.0125	-0.2535	15.01	0.6427	0.0111	-0.0253	-0.0000894
0.16	5	176.03	1772	82.94	803	12.15	8.22	2.26	0.0001191	0.0084	-0.0947	12.63	0.4114	0.0155	-0.0180	-0.0000887
0.16	10	177.25	1766	83.17	803	12.85	13.60	2.83	0.0001218	0.0084	-0.1050	12.48	0.4066	0.0155	-0.0179	-0.0000860
0.16	20	179.36	1756	83.18	818	13.67	23.25	3.54	0.0001222	0.0085	-0.1207	12.53	0.4116	0.0155	-0.0178	-0.0000856
0.16	38	181.68	1752	83.63	838	14.36	39.05	4.38	0.0001273	0.0084	-0.1144	11.71	0.4029	0.0158	-0.0176	-0.0000804
0.16	50	183.03	1751	83.76	835	14.68	49.03	4.80	0.0001283	0.0085	-0.1213	11.81	0.4049	0.0158	-0.0176	-0.0000795
0.16	100	186.96	1748	83.75	859	15.11	88.82	6.05	0.0001318	0.0086	-0.1292	11.46	0.4065	0.0160	-0.0176	-0.0000759
0.16	200	191.81	1727	83.46	860	15.42	160.93	7.45	0.0001374	0.0087	-0.1380	10.89	0.4115	0.0160	-0.0175	-0.0000704

**Table 17: Key figures of timing for volatility clustering based on pathwise estimation.** The table shows the moments of the pathwise return distribution, risk- and performance figures of the SMA trading rules if the mean level of volatility clustering is applied in the underlying benchmark (daily basis). ATH stands for all-time-high, ATL for all-time-low, PiT for point-in-time, MLS for maximum loss sequence, AWD for average win trade duration, ALD for average loss trade duration, and MaxDD for maximum drawdown.

$\sigma$	SMA	ATH	-PiT	ATL	-PiT	Mean Ret.	Vol.	Skew	Kurt.	MaxDD	Sharpe	VarR(5%)
0.39	5	400.44	1642	63.22	845	0.0002157	0.0198	-0.15055	5.97	1.0832	0.0118	-0.0312
0.39	10	400.45	1647	63.22	850	0.0002157	0.0198	-0.15055	5.97	1.0832	0.0118	-0.0312
0.39	20	400.54	1654	63.22	860	0.0002157	0.0198	-0.15055	5.97	1.0832	0.0118	-0.0312
0.39	38	400.79	1662	63.22	878	0.0002157	0.0198	-0.15055	5.97	1.0832	0.0118	-0.0312
0.39	50	400.79	1674	63.22	890	0.0002157	0.0198	-0.15055	5.97	1.0832	0.0118	-0.0312
0.39	100	400.79	1724	63.22	940	0.0002157	0.0198	-0.15055	5.97	1.0832	0.0118	-0.0312
0.39	200	400.79	1824	60.69	931	0.0002157	0.0198	-0.15055	5.97	1.0832	0.0118	-0.0312
0.26	5	269.16	1760	74.79	733	0.0002089	0.0135	-0.10061	5.80	0.6846	0.0162	-0.0212
0.26	10	269.16	1765	74.79	738	0.0002089	0.0135	-0.10061	5.80	0.6846	0.0162	-0.0212
0.26	20	269.21	1771	74.79	748	0.0002089	0.0135	-0.10061	5.80	0.6846	0.0162	-0.0212
0.26	38	269.32	1782	74.79	766	0.0002089	0.0135	-0.10061	5.80	0.6846	0.0162	-0.0212
0.26	50	269.32	1794	74.79	778	0.0002089	0.0135	-0.10061	5.80	0.6846	0.0162	-0.0212
0.26	100	269.32	1844	74.79	828	0.0002089	0.0135	-0.10061	5.80	0.6846	0.0162	-0.0212
0.26	200	269.32	1944	72.62	802	0.0002089	0.0135	-0.10061	5.80	0.6846	0.0162	-0.0212
0.16	5	222.86	1902	82.13	561	0.0002078	0.0099	-0.07657	5.89	0.4546	0.0217	-0.0155
0.16	10	222.86	1907	82.13	566	0.0002078	0.0099	-0.07657	5.89	0.4546	0.0217	-0.0155
0.16	20	222.90	1913	82.13	576	0.0002078	0.0099	-0.07657	5.89	0.4546	0.0217	-0.0155
0.16	38	222.99	1921	82.13	594	0.0002078	0.0099	-0.07657	5.89	0.4546	0.0217	-0.0155
0.16	50	222.99	1933	82.13	606	0.0002078	0.0099	-0.07657	5.89	0.4546	0.0217	-0.0155
0.16	100	222.99	1983	82.13	656	0.0002078	0.0099	-0.07657	5.89	0.4546	0.0217	-0.0155
0.16	200	222.99	2083	80.67	645	0.0002078	0.0099	-0.07657	5.89	0.4546	0.0217	-0.0155

**Table 18: Key figures of benchmark for volatility clustering based on pathwise estimation.** The table shows the moments of the pathwise return distribution of the buy-and-hold approach if the mean volatility clustering level is applied on the underlying asset (daily basis). ATH stands for all-time-high, ATL for all-time-low, PiT for point-in-time, and MaxDD for maximum drawdown.

$\sigma$	SMA	Timing Distribution										Benchmark Distribution					
		Mean Ret	Vol	Skew	Kurt	VaR(5%)	Sharpe	SD	Exp. Exc. Ret.	Mean Ret	Vol	Skew	Kurt	VaR(5%)	Sharpe		
0.39	5	-0.0422	0.9382	-2.88	10.49	-0.9678	-0.0449	-1	-0.0899	0.0520	0.3894	-5.0667	85.83	-0.1191	0.1335		
0.39	10	-0.0395	0.9308	-2.99	11.32	-0.9624	-0.0424	-1	-0.0864	0.0520	0.3894	-5.0667	85.83	-0.1191	0.1335		
0.39	20	-0.0352	0.8998	-3.00	11.48	-0.9386	-0.0392	-1	-0.0836	0.0520	0.3894	-5.0667	85.83	-0.1191	0.1335		
0.39	38	-0.0337	0.9053	-3.09	12.11	-0.9410	-0.0372	-1	-0.0810	0.0520	0.3894	-5.0667	85.83	-0.1191	0.1335		
0.39	50	-0.0330	0.9017	-3.07	11.96	-0.9394	-0.0365	-1	-0.0805	0.0520	0.3894	-5.0667	85.83	-0.1191	0.1335		
0.39	100	-0.0282	0.8808	-3.12	12.45	-0.9218	-0.0320	0	-0.0762	0.0520	0.3894	-5.0667	85.83	-0.1191	0.1335		
0.39	200	-0.0237	0.8615	-3.22	13.36	-0.8968	-0.0275	-1	-0.0718	0.0520	0.3894	-5.0667	85.83	-0.1191	0.1335		
0.26	5	0.0161	0.4474	-6.55	54.93	-0.0773	0.0360	-1	-0.0340	0.0512	0.2661	-8.0876	204.53	-0.0633	0.1922		
0.26	10	0.0206	0.3814	-6.93	67.06	-0.0757	0.0540	-1	-0.0301	0.0512	0.2661	-8.0876	204.53	-0.0633	0.1922		
0.26	20	0.0192	0.4173	-6.89	63.12	-0.0735	0.0461	-1	-0.0312	0.0512	0.2661	-8.0876	204.53	-0.0633	0.1922		
0.26	38	0.0219	0.3829	-7.01	68.71	-0.0729	0.0572	-1	-0.0287	0.0512	0.2661	-8.0876	204.53	-0.0633	0.1922		
0.26	50	0.0218	0.3903	-6.92	66.98	-0.0726	0.0558	-1	-0.0288	0.0512	0.2661	-8.0876	204.53	-0.0633	0.1922		
0.26	100	0.0229	0.3882	-6.75	64.94	-0.0728	0.0591	-1	-0.0277	0.0512	0.2661	-8.0876	204.53	-0.0633	0.1922		
0.26	200	0.0244	0.3833	-6.70	66.29	-0.0747	0.0636	0	-0.0265	0.0512	0.2661	-8.0876	204.53	-0.0633	0.1922		
0.16	5	0.0288	0.1947	-9.93	205.73	-0.0409	0.1480	-1	-0.0229	0.0519	0.1629	-0.3321	6.03	-0.0317	0.3187		
0.16	10	0.0298	0.1735	-7.43	156.74	-0.0388	0.1720	-1	-0.0220	0.0519	0.1629	-0.3321	6.03	-0.0317	0.3187		
0.16	20	0.0293	0.2144	-10.69	209.14	-0.0381	0.1365	-1	-0.0223	0.0519	0.1629	-0.3321	6.03	-0.0317	0.3187		
0.16	38	0.0314	0.1675	-6.18	138.83	-0.0379	0.1874	-1	-0.0205	0.0519	0.1629	-0.3321	6.03	-0.0317	0.3187		
0.16	50	0.0313	0.1852	-8.48	186.83	-0.0384	0.1692	-1	-0.0204	0.0519	0.1629	-0.3321	6.03	-0.0317	0.3187		
0.16	100	0.0321	0.1908	-7.76	161.38	-0.0387	0.1683	-1	-0.0196	0.0519	0.1629	-0.3321	6.03	-0.0317	0.3187		
0.16	200	0.0336	0.1888	-6.46	126.82	-0.0385	0.1782	-1	-0.0182	0.0519	0.1629	-0.3321	6.03	-0.0317	0.3187		

**Table 19: Key figures of timing and benchmark if volatility clustering is applied; based on estimation of terminal values.** The table shows the moments of the return distribution of terminal results of timing and the corresponding buy-and-hold approach if the mean volatility clustering level is applied to the underlying asset (annual basis). SD stands for stochastic dominance: in case of first-order dominance of timing (buy-and-hold) the value is 1 (-1); in case of second-order dominance of timing (buy-and-hold) the value is 2 (-2). If no dominance can be detected, the value is 0.

Country	$\mu$	$\sigma$	$\varphi$	$\beta$	Scoring	Prediction
Argentina	0.1513	0.3541	0.0426	0.8775	0.5	-
Australia	0.0360	0.1628	-0.0332	0.9021	1.5	
Austria	0.0769	0.2422	0.0529	0.8476	1	
Belgium	-0.0196	0.2160	0.0645	0.8436	3	+
Brazil	0.1492	0.3161	0.0056	0.9060	0.5	-
Canada	0.0105	0.2158	-0.0828	0.9263	1.5	
China	0.2051	0.3528	0.0746	0.9120	0.5	-
Europe	-0.0624	0.2558	-0.0549	0.8861	3.5	++
France	-0.0598	0.2511	-0.0545	0.8929	3.5	++
Germany	-0.0145	0.2643	-0.0393	0.8940	2.5	(+)
Greece	-0.1160	0.2810	0.0879	0.8951	2.5	(+)
Hong Kong	0.0295	0.2648	-0.0233	0.9274	0.5	-
Hungary	0.0930	0.2678	0.0678	0.8767	0.5	-
India	0.1381	0.2711	0.0800	0.8269	0	--
Indonesia	0.1647	0.2435	0.1251	0.8046	1	
Italy	-0.0825	0.2368	-0.0100	0.8860	3.5	++
Japan	-0.0691	0.2591	-0.0356	0.8963	3.5	++
Mexico	0.1492	0.2302	0.1038	0.9049	1.5	
The Netherlands	-0.0712	0.2626	-0.0259	0.8813	2.5	
Pakistan	0.1591	0.2488	0.1007	0.7871	1	
Peru	0.2257	0.2367	0.2064	0.7350	1	
The Philippines	0.0702	0.2283	0.1195	0.8106	1	
Poland	0.0165	0.2660	0.0463	0.9424	0.5	-
Russia	0.1881	0.3805	0.0933	0.8511	0	--
Saudi Arabia	0.1154	0.2760	0.0477	0.8489	0	--
Singapore	0.0307	0.2106	0.0146	0.8920	1.5	
South Africa	0.1154	0.2316	0.0388	0.8941	1.5	
South Korea	0.0829	0.2831	0.0172	0.9180	0.5	-
Spain	-0.0077	0.2442	-0.0329	0.8839	3.5	++
Sweden	-0.0231	0.2658	-0.0259	0.9085	2.5	
Switzerland	-0.0191	0.2092	0.0084	0.8585	3	+
Thailand	0.0700	0.2394	0.0299	0.7956	1	
Turkey	0.1363	0.3938	0.0069	0.8762	0.5	-
United Kingdom	-0.0204	0.2104	-0.0733	0.8813	3.5	++
U.S.A.	-0.0301	0.2188	-0.1027	0.9172	3.5	++

**Table 20: Scoring result of the 35 selected leading equity indices.** For every index, a simple scoring model is applied as a forecast on which markets should perform best (++) or worst (-). Depending on their stochastic parameters, every market receives points with respect to the importance of the parameters: for negative drifts  $\mu$  (2 points), for below average volatility  $\sigma$  (1 point) and for above average clustering of returns  $\beta$  (0.5 points). This simple scoring model is able to predict most of the best and worst performing countries.

Country	5	10	20	38	50	100	200
Argentina	-0.1576	-0.1591	-0.1519	-0.1447	-0.1516	-0.1587	-0.1530
Australia	-0.0222	-0.0195	-0.0211	-0.0206	-0.0199	-0.0198	-0.0189
Austria	-0.1075	-0.0897	-0.0824	-0.0621	-0.0665	-0.0585	-0.0563
Belgium	-0.0309	-0.0351	-0.0357	-0.0389	-0.0321	-0.0364	-0.0316
Brazil	-0.1468	-0.1391	-0.1335	-0.1280	-0.1210	-0.1159	-0.1055
Canada	-0.0296	-0.0291	-0.0273	-0.0334	-0.0310	-0.0254	-0.0256
China	-0.2277	-0.2004	-0.2012	-0.1608	-0.1707	-0.1627	-0.1233
Europe	0.0215	0.0158	0.0184	0.0172	0.0163	0.0195	0.0297
France	0.0004	0.0112	0.0051	0.0162	0.0119	0.0116	0.0106
Germany	-0.0240	-0.0296	-0.0161	-0.0269	-0.0343	-0.0298	-0.0342
Greece	-0.0034	0.0109	0.0088	0.0178	0.0121	0.0167	0.0136
Hong Kong	-0.0431	-0.0533	-0.0483	-0.0560	-0.0548	-0.0508	-0.0629
Hungary	-0.1007	-0.0875	-0.0853	-0.0805	-0.0769	-0.0709	-0.0671
India	-0.0938	-0.0948	-0.0967	-0.0950	-0.0870	-0.0772	-0.0585
Indonesia	-0.0797	-0.0700	-0.0658	-0.0607	-0.0558	-0.0478	-0.0348
Italy	0.0333	0.0336	0.0380	0.0355	0.0394	0.0385	0.0431
Japan	0.0315	0.0322	0.0402	0.0443	0.0353	0.0471	0.0427
Mexico	-0.0634	-0.0664	-0.0573	-0.0469	-0.0467	-0.0438	-0.0338
The Netherlands	0.0134	0.0147	0.0053	0.0150	0.0013	0.0030	0.0147
Pakistan	-0.0695	-0.0631	-0.0590	-0.0555	-0.0496	-0.0441	-0.0360
Peru	-0.1021	-0.0942	-0.0779	-0.0654	-0.0645	-0.0505	-0.0306
The Philippines	-0.0463	-0.0441	-0.0392	-0.0405	-0.0400	-0.0376	-0.0410
Poland	-0.0631	-0.0621	-0.0649	-0.0585	-0.0632	-0.0534	-0.0572
Russia	-0.2313	-0.2127	-0.2011	-0.1821	-0.1853	-0.1471	-0.1066
Saudi Arabia	-0.1347	-0.1312	-0.1105	-0.1027	-0.0996	-0.0806	-0.0450
Singapore	-0.0265	-0.0247	-0.0251	-0.0296	-0.0284	-0.0283	-0.0290
South Africa	-0.0699	-0.0687	-0.0582	-0.0584	-0.0542	-0.0603	-0.0492
South Korea	-0.0749	-0.0814	-0.0717	-0.0717	-0.0738	-0.0606	-0.0654
Spain	-0.0255	-0.0195	-0.0243	-0.0328	-0.0227	-0.0351	-0.0290
Sweden	-0.0221	-0.0354	-0.0392	-0.0251	-0.0355	-0.0303	-0.0268
Switzerland	0.0057	0.0040	0.0032	0.0081	0.0021	0.0053	0.0027
Thailand	-0.0536	-0.0540	-0.0475	-0.0458	-0.0417	-0.0432	-0.0381
Turkey	-0.1969	-0.1990	-0.2060	-0.2015	-0.2054	-0.1748	-0.1760
United Kingdom	0.0022	0.0045	0.0017	0.0040	0.0046	0.0046	-0.0009
U.S.A.	0.0078	0.0070	0.0088	0.0023	0.0050	0.0085	0.0037

**Table 21: Average excess return from timing in the 35 selected leading equity indices.** For every index, a non-parametric bootstrap is run with 1,000 different paths. The table shows the average excess return from timing over the buy-and-hold approach (positive values imply an over-return from timing). The numbers are given as annual log-returns based on the distribution of terminal values.

Country	5	10	20	38	50	100	200
Argentina	0.7950	0.7865	0.7608	0.7249	0.7518	0.7693	0.7471
Australia	0.0555	-0.0386	0.0071	-0.0438	-0.0476	0.0416	-0.0451
Austria	0.6122	0.4829	0.4350	0.2865	0.3491	0.2707	0.2991
Belgium	0.2246	0.2890	0.2845	0.2967	0.2058	0.2444	0.1852
Brazil	0.7442	0.7097	0.6874	0.6388	0.6175	0.5953	0.5455
Canada	0.1744	0.1509	0.1127	0.2009	0.1850	0.0956	0.0380
China	0.9563	0.8779	0.9082	0.7491	0.7935	0.7698	0.6071
Europe	0.2861	0.3473	0.3145	0.3049	0.3103	0.2690	0.1160
France	0.3456	0.2832	0.3358	0.1697	0.2371	0.2011	0.1968
Germany	0.3481	0.4060	0.2482	0.3538	0.4012	0.3391	0.3231
Greece	0.3921	0.2728	0.2836	0.1984	0.2476	0.2090	0.1993
Hong Kong	0.3986	0.4953	0.4367	0.4819	0.4553	0.4017	0.5219
Hungary	0.5792	0.4858	0.4865	0.4477	0.4314	0.3755	0.3639
India	0.4939	0.5291	0.5336	0.5061	0.4624	0.4044	0.2476
Indonesia	0.3500	0.2458	0.2363	0.2341	0.1907	0.1374	-0.0288
Italy	0.1891	0.2023	0.1480	0.1870	0.1320	0.1499	0.0450
Japan	0.2905	0.2634	0.1819	0.1248	0.2687	0.0720	0.1438
Mexico	0.2540	0.3269	0.2157	0.0801	0.1138	0.1529	0.0077
The Netherlands	0.2338	0.2626	0.3394	0.2218	0.3787	0.3345	0.2100
Pakistan	0.2159	0.1668	0.1519	0.1564	0.0728	0.0563	0.0199
Peru	0.5389	0.5026	0.3689	0.3196	0.3260	0.2408	-0.0085
The Philippines	0.3034	0.2611	0.1718	0.1896	0.1931	0.1420	0.1678
Poland	0.4765	0.4724	0.4848	0.4015	0.4604	0.3697	0.3996
Russia	0.9277	0.8907	0.8557	0.7745	0.8026	0.6525	0.4871
Saudi Arabia	0.6622	0.6462	0.5411	0.5170	0.5119	0.4374	0.1709
Singapore	0.1883	0.1365	0.1598	0.1970	0.1564	0.0982	0.1105
South Africa	0.4049	0.3877	0.2902	0.2936	0.2441	0.3398	0.2210
South Korea	0.4641	0.5028	0.4289	0.4275	0.4321	0.3105	0.3502
Spain	0.2835	0.2256	0.2622	0.3398	0.2336	0.3264	0.2572
Sweden	0.3416	0.4575	0.4838	0.3346	0.4439	0.3735	0.3181
Switzerland	0.0758	0.1396	0.1390	0.0131	0.1203	0.0273	0.0571
Thailand	0.3173	0.3416	0.2465	0.2435	0.1981	0.2105	0.1401
Turkey	0.8515	0.8465	0.8563	0.8495	0.8651	0.7462	0.7488
United Kingdom	0.1362	0.0702	0.1496	0.1362	0.1152	0.0780	0.1406
U.S.A.	0.0574	0.0500	-0.0140	0.1749	0.1099	0.0191	0.0409

**Table 22: Average excess volatility from timing in the 35 selected leading equity indices.** For every index, a non-parametric bootstrap is run with 1,000 different paths. The table shows the average excess volatility from timing over the buy-and-hold approach (positive values imply an increased volatility from timing). The annual numbers are based on the distribution of terminal values.

Country	5	10	20	38	50	100	200
Argentina	-0.5096	-0.5115	-0.5070	-0.5030	-0.5073	-0.5125	-0.5090
Australia	-0.1459	-0.0670	-0.1182	-0.0697	-0.0589	-0.1291	-0.0536
Austria	-0.3028	-0.2756	-0.2620	-0.2079	-0.2271	-0.1975	-0.1998
Belgium	0.0577	0.0536	0.0522	0.0468	0.0533	0.0472	0.0526
Brazil	-0.5225	-0.5167	-0.5121	-0.5084	-0.5017	-0.4969	-0.4863
Canada	-0.0468	-0.0454	-0.0396	-0.0561	-0.0504	-0.0330	-0.0302
China	-0.6271	-0.6078	-0.6078	-0.5750	-0.5838	-0.5768	-0.5349
Europe	0.1257	0.1283	0.1261	0.1221	0.1216	0.1180	0.0937
France	0.1242	0.1312	0.1304	0.1143	0.1225	0.1127	0.1091
Germany	-0.0267	-0.0280	-0.0273	-0.0306	-0.0357	-0.0376	-0.0476
Greece	0.2988	0.3000	0.2985	0.2969	0.2970	0.2972	0.2884
Hong Kong	-0.1834	-0.1877	-0.1870	-0.1928	-0.1941	-0.1947	-0.1973
Hungary	-0.3792	-0.3657	-0.3627	-0.3568	-0.3518	-0.3429	-0.3369
India	-0.4769	-0.4795	-0.4820	-0.4789	-0.4661	-0.4479	-0.3933
Indonesia	-0.5424	-0.4941	-0.4818	-0.4703	-0.4384	-0.3840	-0.0974
Italy	0.2177	0.2222	0.2160	0.2222	0.2141	0.2179	0.1856
Japan	0.1397	0.1345	0.1282	0.1182	0.1416	0.1030	0.1212
Mexico	-0.5325	-0.5529	-0.5089	-0.4144	-0.4370	-0.4509	-0.2888
The Netherlands	0.1559	0.1649	0.1628	0.1564	0.1632	0.1581	0.1530
Pakistan	-0.3984	-0.3547	-0.3338	-0.3285	-0.2294	-0.1892	-0.0979
Peru	-0.8415	-0.8254	-0.7701	-0.7314	-0.7323	-0.6635	-0.2590
The Philippines	-0.3214	-0.3180	-0.3082	-0.3112	-0.3099	-0.3038	-0.3125
Poland	-0.1305	-0.1294	-0.1321	-0.1312	-0.1320	-0.1265	-0.1294
Russia	-0.4958	-0.4812	-0.4714	-0.4534	-0.4571	-0.4148	-0.3528
Saudi Arabia	-0.3203	-0.3147	-0.2762	-0.2620	-0.2570	-0.2136	-0.0118
Singapore	-0.1685	-0.1669	-0.1665	-0.1757	-0.1759	-0.1811	-0.1820
South Africa	-0.4773	-0.4748	-0.4504	-0.4510	-0.4373	-0.4581	-0.4230
South Korea	-0.3225	-0.3293	-0.3194	-0.3195	-0.3223	-0.3061	-0.3128
Spain	-0.0326	-0.0278	-0.0330	-0.0390	-0.0335	-0.0446	-0.0431
Sweden	0.0040	-0.0010	-0.0031	-0.0019	-0.0028	-0.0046	-0.0074
Switzerland	-0.0099	0.0038	0.0012	-0.0276	-0.0072	-0.0325	-0.0281
Thailand	-0.2993	-0.2997	-0.2878	-0.2842	-0.2739	-0.2777	-0.2616
Turkey	-0.4366	-0.4387	-0.4436	-0.4405	-0.4424	-0.4256	-0.4265
United Kingdom	0.0032	-0.0107	0.0053	0.0084	0.0046	-0.0074	-0.0043
U.S.A.	0.0298	0.0239	-0.0030	0.0479	0.0385	0.0152	0.0070

**Table 23: Average excess Sharpe ratios from timing in the 35 selected leading equity indices.** For every index, a non-parametric bootstrap is run with 1,000 different paths. The table shows the average excess Sharpe ratios from timing over the buy-and-hold approach (positive values imply an excess risk-adjusted return from timing. However, it is difficult to interpret negative Sharpe values (cf. Scholz & Wilkens 2006). The annual values are based on the distribution of terminal returns.

Country	5	10	20	38	50	100	200
Argentina	289	205	145	104	91	64	46
Australia	295	210	149	108	95	66	47
Austria	293	208	146	105	91	63	43
Belgium	297	211	149	108	94	68	47
Brazil	295	210	149	108	95	68	47
Canada	296	212	150	108	96	66	46
China	291	206	145	104	89	62	42
Europe	295	211	150	109	95	67	46
France	297	211	150	108	94	67	47
Germany	295	211	150	109	95	67	48
Greece	294	209	148	106	93	66	47
Hong Kong	291	208	147	107	93	67	48
Hungary	296	211	150	108	94	68	48
India	292	206	144	105	91	62	43
Indonesia	288	202	142	102	87	59	39
Italy	295	210	149	107	93	65	45
Japan	294	210	148	107	93	64	45
Mexico	290	205	145	104	90	62	42
The Netherlands	296	210	149	108	95	66	46
Pakistan	282	199	138	97	84	57	38
Peru	287	200	138	95	81	52	32
The Philippines	290	205	144	104	91	63	44
Poland	294	210	149	108	95	67	48
Russia	287	203	141	101	87	59	39
Saudi Arabia	275	191	130	90	77	50	31
Singapore	294	210	148	108	96	68	48
South Africa	295	210	148	107	92	64	45
South Korea	289	206	146	106	91	64	45
Spain	296	211	149	109	95	67	48
Sweden	296	210	149	108	94	67	47
Switzerland	297	211	149	109	95	67	46
Thailand	292	207	146	105	91	63	44
Turkey	294	209	148	107	93	65	45
United Kingdom	294	210	148	108	93	66	47
U.S.A.	291	208	148	106	93	65	45

**Table 24: Average number of trades from timing in the 35 selected leading equity indices.** For every index, a non-parametric bootstrap is run with 1,000 different paths. The table shows the average numbers of trades from timing in the course of 10 years of simulated trading.

Country	5	10	20	38	50	100	200
Argentina	0.3435	0.3063	0.2681	0.2362	0.2244	0.1939	0.1757
Australia	0.3469	0.3088	0.2704	0.2394	0.2276	0.2008	0.1782
Austria	0.3616	0.3268	0.2902	0.2612	0.2482	0.2265	0.2040
Belgium	0.3324	0.2930	0.2547	0.2214	0.2085	0.1801	0.1635
Brazil	0.3454	0.3078	0.2703	0.2390	0.2240	0.2006	0.1801
Canada	0.3406	0.3015	0.2617	0.2287	0.2160	0.1944	0.1757
China	0.3577	0.3228	0.2885	0.2597	0.2474	0.2232	0.2047
Europe	0.3106	0.2680	0.2265	0.1906	0.1758	0.1445	0.1204
France	0.3125	0.2717	0.2318	0.1968	0.1829	0.1503	0.1290
Germany	0.3256	0.2862	0.2458	0.2125	0.1968	0.1696	0.1441
Greece	0.3079	0.2693	0.2284	0.1970	0.1824	0.1500	0.1285
Hong Kong	0.3302	0.2919	0.2524	0.2177	0.2043	0.1723	0.1548
Hungary	0.3399	0.3030	0.2649	0.2337	0.2228	0.1958	0.1772
India	0.3597	0.3238	0.2866	0.2565	0.2447	0.2221	0.2014
Indonesia	0.3679	0.3330	0.2976	0.2693	0.2617	0.2372	0.2250
Italy	0.3087	0.2664	0.2241	0.1877	0.1750	0.1430	0.1137
Japan	0.3096	0.2667	0.2269	0.1921	0.1787	0.1478	0.1212
Mexico	0.3617	0.3265	0.2897	0.2622	0.2521	0.2275	0.2109
The Netherlands	0.3128	0.2726	0.2326	0.1943	0.1803	0.1505	0.1283
Pakistan	0.3802	0.3451	0.3117	0.2849	0.2725	0.2462	0.2312
Peru	0.3874	0.3549	0.3229	0.2995	0.2857	0.2674	0.2524
The Philippines	0.3339	0.2971	0.2589	0.2278	0.2157	0.1912	0.1712
Poland	0.3262	0.2898	0.2508	0.2189	0.2072	0.1785	0.1564
Russia	0.3716	0.3371	0.3044	0.2739	0.2639	0.2416	0.2309
Saudi Arabia	0.3967	0.3641	0.3339	0.3056	0.2940	0.2720	0.2601
Singapore	0.3318	0.2939	0.2561	0.2230	0.2099	0.1816	0.1607
South Africa	0.3501	0.3130	0.2756	0.2446	0.2340	0.2060	0.1862
South Korea	0.3482	0.3093	0.2706	0.2391	0.2288	0.2001	0.1817
Spain	0.3291	0.2892	0.2510	0.2146	0.2020	0.1754	0.1524
Sweden	0.3228	0.2830	0.2421	0.2094	0.1939	0.1659	0.1468
Switzerland	0.3214	0.2807	0.2402	0.2053	0.1922	0.1613	0.1399
Thailand	0.3421	0.3049	0.2693	0.2377	0.2251	0.2005	0.1818
Turkey	0.3408	0.3030	0.2659	0.2363	0.2250	0.1993	0.1817
United Kingdom	0.3221	0.2812	0.2425	0.2068	0.1916	0.1614	0.1425
U.S.A.	0.3203	0.2801	0.2391	0.2054	0.1922	0.1624	0.1401

**Table 25: Average hit ratio from timing in the 35 selected leading equity indices.**

For every index, a non-parametric bootstrap is run with 1,000 different paths. The table shows the average hit ratio, i.e. number of win trades with respect to all trades, from timing in the course of 10 years of simulated trading.

Country	5	10	20	38	50	100	200
Argentina	0.5264	0.5271	0.5309	0.5347	0.5356	0.5470	0.5670
Australia	0.5342	0.5364	0.5412	0.5501	0.5571	0.5780	0.6001
Austria	0.5492	0.5587	0.5752	0.5976	0.6080	0.6465	0.6901
Belgium	0.5171	0.5161	0.5143	0.5121	0.5130	0.5207	0.5385
Brazil	0.5299	0.5327	0.5377	0.5458	0.5518	0.5730	0.6041
Canada	0.5251	0.5252	0.5270	0.5289	0.5377	0.5544	0.5787
China	0.5395	0.5486	0.5642	0.5823	0.5910	0.6207	0.6602
Europe	0.4890	0.4777	0.4654	0.4486	0.4374	0.4159	0.3927
France	0.4930	0.4839	0.4733	0.4605	0.4532	0.4321	0.4139
Germany	0.5068	0.5007	0.4966	0.4919	0.4889	0.4841	0.4750
Greece	0.4847	0.4770	0.4667	0.4548	0.4493	0.4187	0.3927
Hong Kong	0.5080	0.5065	0.5029	0.5005	0.4980	0.4954	0.5014
Hungary	0.5201	0.5270	0.5345	0.5429	0.5492	0.5701	0.5985
India	0.5456	0.5512	0.5608	0.5773	0.5873	0.6163	0.6491
Indonesia	0.5547	0.5648	0.5809	0.6033	0.6184	0.6573	0.7123
Italy	0.4902	0.4761	0.4579	0.4411	0.4325	0.4034	0.3657
Japan	0.4878	0.4769	0.4625	0.4456	0.4357	0.4137	0.3802
Mexico	0.5464	0.5539	0.5683	0.5891	0.6006	0.6344	0.6813
The Netherlands	0.4925	0.4827	0.4717	0.4580	0.4497	0.4304	0.4096
Pakistan	0.5657	0.5778	0.5975	0.6238	0.6361	0.6746	0.7210
Peru	0.5731	0.5947	0.6223	0.6575	0.6715	0.7237	0.7843
The Philippines	0.5146	0.5166	0.5210	0.5259	0.5294	0.5447	0.5692
Poland	0.5043	0.5052	0.5072	0.5096	0.5098	0.5156	0.5231
Russia	0.5563	0.5667	0.5839	0.6078	0.6208	0.6598	0.7155
Saudi Arabia	0.5836	0.5998	0.6228	0.6527	0.6667	0.7066	0.7572
Singapore	0.5139	0.5129	0.5139	0.5135	0.5178	0.5244	0.5383
South Africa	0.5321	0.5380	0.5468	0.5578	0.5632	0.5800	0.6057
South Korea	0.5320	0.5319	0.5356	0.5416	0.5472	0.5617	0.5781
Spain	0.5121	0.5083	0.5058	0.5016	0.5016	0.5048	0.5042
Sweden	0.5015	0.4966	0.4905	0.4829	0.4779	0.4666	0.4742
Switzerland	0.5033	0.4962	0.4876	0.4779	0.4772	0.4692	0.4664
Thailand	0.5230	0.5279	0.5351	0.5439	0.5487	0.5642	0.5845
Turkey	0.5228	0.5271	0.5322	0.5426	0.5469	0.5635	0.5904
United Kingdom	0.5024	0.4951	0.4869	0.4763	0.4684	0.4502	0.4530
U.S.A.	0.5010	0.4934	0.4860	0.4794	0.4751	0.4651	0.4578

**Table 26: Average exposure time from timing in the 35 selected leading equity indices.** For every index, a non-parametric bootstrap is run with 1,000 different paths. The table shows the average relative amount of time the trading rule is exposed to the risky underlying. The time horizon is 10 years of simulated trading.

Country	5	10	20	38	50	100	200
Argentina	2.07	2.49	3.12	3.85	4.20	5.37	6.87
Australia	2.11	2.59	3.24	4.02	4.42	5.88	7.80
Austria	2.18	2.69	3.45	4.48	5.07	6.75	9.90
Belgium	2.09	2.54	3.15	3.85	4.19	5.25	6.55
Brazil	2.13	2.62	3.25	4.08	4.59	5.94	7.77
Canada	2.09	2.55	3.19	3.95	4.37	5.46	6.73
China	2.17	2.67	3.40	4.30	4.86	6.55	9.65
Europe	1.97	2.36	2.83	3.34	3.54	4.11	4.70
France	1.99	2.39	2.87	3.38	3.62	4.30	4.83
Germany	2.02	2.42	2.95	3.54	3.85	4.56	5.45
Greece	2.03	2.42	2.92	3.44	3.69	4.50	4.94
Hong Kong	2.04	2.45	2.99	3.62	3.93	4.91	5.81
Hungary	2.17	2.64	3.34	4.19	4.62	6.01	7.91
India	2.14	2.65	3.36	4.22	4.71	6.16	8.67
Indonesia	2.22	2.76	3.58	4.67	5.18	7.29	10.74
Italy	1.94	2.31	2.77	3.28	3.48	4.13	4.73
Japan	1.93	2.29	2.73	3.20	3.42	3.86	4.30
Mexico	2.18	2.71	3.44	4.40	4.88	6.69	9.49
The Netherlands	2.01	2.40	2.88	3.51	3.77	4.41	5.21
Pakistan	2.21	2.78	3.60	4.69	5.33	7.69	11.89
Peru	2.18	2.71	3.49	4.55	5.25	7.40	11.57
The Philippines	2.15	2.59	3.22	3.92	4.34	5.40	6.90
Poland	2.11	2.52	3.08	3.71	4.04	5.12	6.38
Russia	2.19	2.72	3.48	4.47	4.96	6.92	9.90
Saudi Arabia	2.17	2.72	3.52	4.66	5.36	7.66	12.61
Singapore	2.10	2.54	3.14	3.82	4.14	5.11	6.31
South Africa	2.15	2.64	3.36	4.20	4.67	6.19	8.61
South Korea	2.04	2.49	3.09	3.83	4.14	5.36	6.61
Spain	2.03	2.47	3.00	3.69	4.02	4.85	5.89
Sweden	2.05	2.47	3.02	3.62	3.95	4.76	5.54
Switzerland	1.99	2.39	2.90	3.48	3.72	4.45	5.10
Thailand	2.10	2.56	3.15	3.90	4.30	5.44	6.96
Turkey	2.13	2.59	3.21	3.95	4.34	5.55	7.18
United Kingdom	1.99	2.38	2.88	3.49	3.83	4.53	5.15
U.S.A.	1.99	2.37	2.86	3.42	3.70	4.38	5.10

**Table 27: Average ratio: size of profit- vs. loss trades in the 35 selected leading equity indices.** For every index, a non-parametric bootstrap is run with 1,000 different paths. The table shows ratio of sizes between profit trades to loss trades, in which the size of an average profit trade is always higher compared to an average loss trade. The time horizon is 10 years of simulated trading.

Country	5	10	20	38	50	100	200
Argentina	3.50	4.51	6.03	7.96	9.05	12.40	17.16
Australia	3.60	4.71	6.32	8.53	9.62	13.40	19.47
Austria	3.64	4.79	6.51	8.89	10.37	14.85	23.02
Belgium	3.53	4.57	6.08	7.91	8.97	12.15	15.12
Brazil	3.58	4.67	6.29	8.44	9.65	13.32	18.55
Canada	3.57	4.65	6.25	8.33	9.52	12.19	15.64
China	3.60	4.73	6.45	8.89	10.22	14.92	23.24
Europe	3.43	4.40	5.73	7.40	8.23	10.61	12.84
France	3.46	4.43	5.77	7.40	8.19	10.38	12.74
Germany	3.49	4.51	5.87	7.63	8.57	11.11	14.30
Greece	3.39	4.33	5.67	7.23	7.98	10.46	12.78
Hong Kong	3.47	4.46	5.93	7.78	8.77	12.00	15.89
Hungary	3.53	4.60	6.27	8.41	9.49	13.54	18.81
India	3.61	4.73	6.37	8.53	9.73	13.32	19.89
Indonesia	3.62	4.74	6.47	8.81	9.92	14.29	21.13
Italy	3.42	4.38	5.71	7.26	7.96	10.18	12.29
Japan	3.41	4.35	5.66	7.18	8.09	10.05	12.24
Mexico	3.62	4.71	6.40	8.60	9.83	14.16	20.26
The Netherlands	3.43	4.39	5.74	7.50	8.40	10.73	12.95
Pakistan	3.63	4.75	6.44	8.73	10.09	14.79	23.26
Peru	3.69	4.92	6.89	9.65	11.49	17.71	29.28
The Philippines	3.44	4.42	5.82	7.58	8.54	11.21	13.97
Poland	3.44	4.49	5.90	7.73	8.72	11.80	15.34
Russia	3.64	4.78	6.50	8.84	10.07	14.64	21.41
Saudi Arabia	3.63	4.76	6.53	9.09	10.53	15.85	25.46
Singapore	3.51	4.57	6.03	7.96	9.02	12.05	15.49
South Africa	3.59	4.69	6.33	8.63	9.86	13.79	20.14
South Korea	3.53	4.58	6.11	8.17	9.06	12.08	16.17
Spain	3.50	4.53	5.94	7.82	8.79	11.11	14.23
Sweden	3.49	4.50	5.92	7.69	8.66	11.42	13.67
Switzerland	3.49	4.51	5.91	7.63	8.50	11.04	12.97
Thailand	3.50	4.55	6.03	7.97	9.02	12.12	15.97
Turkey	3.52	4.57	6.15	8.05	9.10	12.47	15.55
United Kingdom	3.46	4.43	5.80	7.60	8.53	11.10	13.65
U.S.A.	3.42	4.38	5.72	7.31	8.17	10.43	12.42

**Table 28: Average ratio: duration of profit- vs. loss trades in the 35 selected leading equity indices.** For every index, a non-parametric bootstrap is run with 1,000 different paths. The table shows ratio of duration between profit trades to loss trades, in which the duration of an average profit trade is always higher compared to an average loss trade. The time horizon is 10 years of simulated trading.

Country	5	10	20	38	50	100	200
Argentina	0.4108	0.4111	0.4053	0.3773	0.4274	0.4118	0.4127
Australia	-0.0266	-0.0408	-0.0432	-0.0384	-0.0382	-0.0449	-0.0468
Austria	0.3739	0.3170	0.2969	0.2076	0.2130	0.1928	0.1904
Belgium	0.0139	0.0204	0.0227	0.0307	0.0186	0.0337	0.0266
Brazil	0.5031	0.4721	0.4809	0.4803	0.4069	0.3881	0.3712
Canada	0.0038	-0.0031	-0.0021	0.0143	-0.0019	-0.0268	-0.0200
China	0.7051	0.6082	0.6169	0.5194	0.5071	0.4666	0.4031
Europe	-0.4878	-0.4890	-0.5066	-0.4850	-0.4960	-0.5185	-0.5738
France	-0.3167	-0.3987	-0.3744	-0.4053	-0.4078	-0.4095	-0.3907
Germany	-0.0915	-0.1125	-0.1520	-0.0812	-0.0791	-0.0873	-0.0483
Greece	-0.4126	-0.4724	-0.4699	-0.5308	-0.4978	-0.5537	-0.5428
Hong Kong	0.0056	0.0129	0.0104	0.0372	0.0476	0.0397	0.0183
Hungary	0.2997	0.2662	0.2720	0.2448	0.2341	0.2308	0.2135
India	0.3225	0.2854	0.3062	0.3238	0.2969	0.2276	0.2141
Indonesia	0.3000	0.2594	0.2390	0.1968	0.1999	0.1446	0.0965
Italy	-0.5867	-0.5857	-0.6233	-0.6364	-0.6364	-0.6570	-0.6844
Japan	-0.5927	-0.5967	-0.6412	-0.6646	-0.6561	-0.7058	-0.7010
Mexico	0.1915	0.1844	0.1810	0.1255	0.1155	0.0901	0.0632
The Netherlands	-0.4077	-0.4404	-0.3893	-0.4249	-0.3936	-0.3873	-0.4669
Pakistan	0.2520	0.2313	0.2168	0.1858	0.1680	0.1579	0.1311
Peru	0.3635	0.3567	0.3003	0.2213	0.2247	0.1692	0.0771
The Philippines	0.0691	0.0768	0.0776	0.0754	0.0692	0.0759	0.0812
Poland	0.1053	0.1000	0.1534	0.1178	0.1192	0.0725	0.0922
Russia	0.7742	0.7126	0.6402	0.6326	0.5952	0.5175	0.3778
Saudi Arabia	0.5132	0.5269	0.4405	0.4224	0.4007	0.3490	0.2112
Singapore	-0.0024	-0.0096	-0.0153	-0.0049	0.0053	-0.0084	-0.0003
South Africa	0.2089	0.1983	0.1529	0.1685	0.1719	0.1716	0.1271
South Korea	0.1443	0.1884	0.1602	0.1498	0.1839	0.1495	0.1677
Spain	-0.0598	-0.0948	-0.0834	-0.0585	-0.0928	-0.0237	-0.0744
Sweden	-0.1569	-0.0909	-0.1065	-0.1283	-0.1083	-0.1498	-0.1526
Switzerland	-0.2347	-0.2307	-0.2289	-0.2578	-0.2409	-0.2497	-0.2471
Thailand	0.1181	0.0784	0.1116	0.0802	0.0859	0.0921	0.0586
Turkey	0.4486	0.5272	0.5401	0.5704	0.5540	0.4626	0.5303
United Kingdom	-0.2219	-0.2123	-0.2309	-0.2481	-0.2580	-0.2698	-0.2465
U.S.A.	-0.2449	-0.2344	-0.2581	-0.2565	-0.2577	-0.2830	-0.2480

**Table 29: Average excess maximum drawdowns from timing in the 35 selected leading equity indices.** For every index, a non-parametric bootstrap is run with 1,000 different paths. The table shows the average excess maximum drawdowns from timing over the buy-and-hold approach (positive values imply peak-to-valley moves in the timing portfolio). The annual numbers are based on the pathwise distribution.

SMA	Coefficient	Std. Error	t-stat.	p	$R^2$	S.E. Regression
5	-0.6342	0.0690	-9.1976	0.0000	0.7194	0.0373
10	-0.6029	0.0650	-9.2766	0.0000	0.7228	0.0352
20	-0.5706	0.0678	-8.4184	0.0000	0.6823	0.0367
38	-0.5276	0.0636	-8.2899	0.0000	0.6756	0.0345
50	-0.5125	0.0669	-7.6634	0.0000	0.6402	0.0362
100	-0.4713	0.0614	-7.6772	0.0000	0.6411	0.0332
200	-0.3924	0.0629	-6.2392	0.0000	0.5412	0.0341

**Table 30: Average excess return dependent on drift.** The OLS regression results show a significant impact from the drift  $\mu$  of the underlying price process on the average excess return from timing: the more positive the drift, the lower the average excess return.

SMA	Coefficient	Std. Error	t-stat.	p	$R^2$	S.E. Regression
5	-1.0657	0.1609	-6.6223	0.0000	0.5706	0.0462
10	-1.0186	0.1510	-6.7463	0.0000	0.5797	0.0433
20	-1.0102	0.1434	-7.0468	0.0000	0.6008	0.0411
38	-0.9179	0.1375	-6.6742	0.0000	0.5744	0.0395
50	-0.9555	0.1288	-7.4184	0.0000	0.6251	0.0370
100	-0.8430	0.1259	-6.6976	0.0000	0.5761	0.0361
200	-0.7357	0.1196	-6.1535	0.0000	0.5343	0.0343

**Table 31: Average excess return dependent on volatility.** The OLS regression results show a significant impact from the volatility  $\sigma$  of the underlying price process on the average excess return from timing: the higher the volatility, the lower the average excess return.

SMA	Coefficient	Std. Error	t-stat.	p	$R^2$	S.E. Regression
5	1.6559	0.3487	4.7482	0.0000	0.4059	0.1889
10	1.5314	0.3565	4.2959	0.0001	0.3587	0.1930
20	1.3650	0.3728	3.6619	0.0009	0.2889	0.2019
38	1.2523	0.3432	3.6485	0.0009	0.2874	0.1859
50	1.0858	0.3741	2.9024	0.0066	0.2034	0.2026
100	1.0934	0.3453	3.1668	0.0033	0.2331	0.1870
200	0.6624	0.3769	1.7576	0.0881	0.0856	0.2041

**Table 32: Average excess volatility dependent on drift.** The OLS regression results show a significant impact from the drift  $\mu$  of the underlying price process on the average excess volatility from timing: the more positive the drift, the higher the average excess volatility.

SMA	Coefficient	Std. Error	t-stat.	p	$R^2$	S.E. Regression
5	4.3400	0.3974	10.9216	0.0000	0.7833	0.1141
10	4.3365	0.3680	11.7829	0.0000	0.8080	0.1056
20	4.3725	0.3409	12.8255	0.0000	0.8329	0.0979
38	3.9958	0.3236	12.3479	0.0000	0.8221	0.0929
50	4.2638	0.2728	15.6291	0.0000	0.8810	0.0783
100	3.8248	0.3317	11.5319	0.0000	0.8012	0.0952
200	3.6184	0.3951	9.1585	0.0000	0.7177	0.1134

**Table 33: Average excess volatility dependent on volatility.** The OLS regression results show a significant impact from the volatility  $\sigma$  of the underlying price process on the average excess volatility from timing: the higher the volatility of the underlying, the higher the average excess volatility.

SMA	Coefficient	Std. Error	t-stat.	p	$R^2$	S.E. Regression
5	-2.9653	0.0892	-33.2543	0.0000	0.9710	0.0483
10	-2.9150	0.1032	-28.2323	0.0000	0.9602	0.0559
20	-2.8157	0.0975	-28.8751	0.0000	0.9619	0.0528
38	-2.7086	0.1040	-26.0406	0.0000	0.9536	0.0563
50	-2.6827	0.1203	-22.3064	0.0000	0.9378	0.0651
100	-2.5242	0.1343	-18.7933	0.0000	0.9145	0.0727
200	-1.9412	0.2183	-8.8914	0.0000	0.7055	0.1182

**Table 34: Average excess Sharpe ratio dependent on drift.** The OLS regression results show a significant impact from the drift  $\mu$  of the underlying price process on the average excess Sharpe ratio from timing: the more positive the drift, the lower the average excess Sharpe ratio.

SMA	Coefficient	Std. Error	t-stat.	p	$R^2$	S.E. Regression
5	-2.0929	0.9187	-2.2780	0.0293	0.1359	0.2637
10	-2.1641	0.9014	-2.4008	0.0222	0.1487	0.2587
20	-2.1282	0.8670	-2.4546	0.0195	0.1544	0.2489
38	-2.1564	0.8300	-2.5980	0.0139	0.1698	0.2382
50	-2.2124	0.8243	-2.6840	0.0113	0.1792	0.2366
100	-2.0155	0.7927	-2.5425	0.0159	0.1638	0.2275
200	-2.1604	0.6593	-3.2766	0.0025	0.2455	0.1893

**Table 35: Average excess Sharpe ratio dependent on volatility.** The OLS regression results show a significant impact from the volatility  $\sigma$  of the underlying price process on the average excess Sharpe ratio from timing: the higher the volatility, the lower the average excess Sharpe ratio.

SMA	Coefficient	Std. Error	t-stat.	p	$R^2$	S.E. Regression
5	2.6722	0.9706	2.7532	0.0095	0.1868	0.2558
10	2.5455	0.9673	2.6317	0.0128	0.1735	0.2549
20	2.3505	0.9417	2.4959	0.0177	0.1588	0.2482
38	2.3146	0.9066	2.5532	0.0155	0.1650	0.2389
50	2.1374	0.9183	2.3276	0.0262	0.1410	0.2420
100	1.8079	0.8900	2.0312	0.0504	0.1111	0.2346
200	0.5733	0.8206	0.6987	0.4896	0.0146	0.2163

**Table 36: Average excess heteroscedasticity.** The OLS regression results show a significant impact from clustered volatilities  $\beta$  of the underlying price process on the average excess Sharpe ratios from timing: the stronger the heteroscedasticity, the higher the average excess Sharpe ratios.

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