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UNIVERSIDADE DO PORTO

# A STUDY ON VOLATILITY AND MOVING AVERAGE TIMING STRATEGIES APPLIED TO THE EUROPEAN STOCK MARKET

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Dissertation

Master in Finance

Supervised by

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2025

# A study on Volatility and Moving Average Timing Strategies applied to the European Stock Market

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July 2025

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# Acknowledgments

I would like to begin by sincerely thanking my supervisor, Professor Júlio Lobão, for his constant support, guidance, and encouragement throughout this dissertation. His enthusiasm in introducing me to such an interesting research topic and his openness in allowing me to explore the connection between behavioural finance and financial markets made this academic journey both enriching and rewarding.

Above all, I dedicate this work to my son, whose presence in my life has been my greatest source of inspiration and strength. His smile, resilience, and the joy he consistently brings remind me of the importance of perseverance, purpose, and balance not only in academia but in life as a whole. This dissertation is, in many ways, for him and because of him.

Finally, I would like to extend my heartfelt thanks to my family and friends, who have supported me unconditionally through every challenge. Your words of encouragement, patience, and care have meant the world to me during this demanding period of my life.

# Abstract

Market efficiency has been increasingly challenged by academics, particularly through the detection of investment strategies capable of generating abnormal returns, from both a return and a risk standpoint.

This dissertation investigates whether moving average timing strategies applied to portfolios of European stocks, sorted by volatility, are able to generate abnormal returns relative to the Capital Asset Pricing Model (CAPM) and to a passive buy-and-hold benchmark. The empirical analysis covers the period 2010–2024, using daily data on the constituent stocks of the STOXX Europe 600 index, with portfolios rebalanced annually into volatility deciles.

A set of moving average portfolios (MAPs), based on different signal lengths, is implemented and their performance evaluated through risk-adjusted returns and CAPM regressions. In this study, the evidence suggests that MAPs' ability to generate abnormal returns is concentrated in the most volatile portfolios, particularly when shorter moving averages are employed. From a theoretical perspective, these findings challenge the weak-form efficiency of European equity markets, while in practical terms they suggest that investors may design systematic trading rules capable of outperforming simple buy-and-hold strategies in specific market segments.

This dissertation contributes to the literature on technical trading rules in European equity markets and provides a foundation for further research across different geographies and historical contexts.

**Keywords:** portfolio optimisation, market efficiency, technical analysis, abnormal returns, moving average strategies

**JEL codes:** G11, G12, G14, G17

# Resumo

A hipótese de eficiência dos mercados tem sido crescentemente desafiada pela literatura académica, nomeadamente através da identificação de estratégias de investimento capazes de gerar retornos anormais, seja em termos absolutos ou ajustados ao risco.

Esta dissertação procura avaliar se estratégias de *market timing* baseadas em médias móveis, aplicadas a carteiras de ações europeias agrupadas por níveis de volatilidade, conseguem gerar retornos anormais em relação ao *Capital Asset Pricing Model* (CAPM) e a uma estratégia passiva de *buy-and-hold*.

O estudo incide sobre o período 2010-2024, recorrendo a dados diários do índice STOXX Europe 600, que integra cerca de 600 ações, com carteiras constituídas anualmente por decis de volatilidade. Foram construídas carteiras de médias móveis (MAPs) com diferentes horizontes temporais - 5, 10, 20, 50, 100 e 200 dias - e avaliado o seu desempenho com base em métricas de risco-retorno e em regressões CAPM.

Os resultados sugerem que a capacidade destas estratégias para gerar retornos anormais se concentra nas carteiras mais voláteis, sobretudo quando utilizadas médias móveis de horizonte temporal mais curto. Do ponto de vista teórico, estas evidências questionam a validade da hipótese de eficiência fraca dos mercados acionistas europeus; do ponto de vista prático, apontam para a possibilidade de os investidores desenharem regras sistemáticas de negociação capazes de superar estratégias de *buy-and-hold* em segmentos específicos do mercado.

Este estudo contribui para a literatura sobre regras técnicas de negociação aplicadas a ações europeias e abre caminho a futuras investigações em diferentes geografias e contextos históricos.

**Palavras-chave:** otimização de portfólios, eficiência de mercado, análise técnica, retornos anormais, estratégias de média móvel

**Códigos JEL:** G11, G12, G14, G17

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# Glossary

AMEX - American Stock Exchange

BETC - Break-even Transaction Costs

CAPM - Capital Asset Pricing Model

CRSP - Center for Research in Security Prices

EMH - Efficient Market Hypothesis

JEL - Journal of Economic Literature

MA - Moving Average

MAP - Moving Average Portfolio

NYSE - New York Stock Exchange

UK - United Kingdom

US - United States (of America)

USA - United States of America

# 1. Introduction

The study of market anomalies has revolutionised how academics and practitioners approach the fields of Economics and Finance, as traditional models of market efficiency (Fama, 1970; Fama, 1991) often fail to explain certain empirical regularities. Early contributions include Shiller's (1981) findings on excess volatility and the subsequent development of behavioural finance (Thaler, 1993; Barberis and Thaler, 2003). Later surveys confirm that the study of anomalies has been reshaping asset pricing theory by incorporating behavioural and institutional perspectives (Malkiel, 2003; Schwert, 2003). In equity markets, well-documented patterns such as the size effect (Banz, 1981), the value premium (Fama and French, 1992), and momentum (Jegadeesh and Titman, 1993) directly challenge the rationale of the Efficient Market Hypothesis (EMH; Fama, 1965), highlighting persistent deviations from efficiency.

Several studies have documented persistent market anomalies, which have significantly influenced the evolution of asset pricing theory. Nevertheless, the Capital Asset Pricing Model (CAPM), first introduced by Sharpe (1964) and Lintner (1965), has remained one of the most widely applied models, valued for its simplicity of application and theoretical robustness despite these challenges.

To test the limits of the EMH, namely its weak and semi-strong forms of efficiency, it is possible to develop trading strategies that generally follow one of two following approaches (or a combination of both). Fundamental analysis, which estimates the future cash flows of an asset or portfolio and discounts them to determine present value, usually at a rate defined by traditional models such as the CAPM or the Fama-French three-factor model. Alternatively, technical analysis, which relies on historical price movements and transaction volumes to develop strategies that attempt to exploit patterns or statistical regularities, such as mean reversion. If a trading rule is consistently profitable under the latter approach, the weak form of EMH is challenged, since prices would fail to incorporate all historical public information (Fama, 1970; Brock et al., 1992; Lo and MacKinlay, 1999; Neely et al., 2014).

The aim of this dissertation is to assess the ability of volatility-conditioned moving average timing strategies, as a form of technical analysis, to generate abnormal returns in European equity markets.

The empirical analysis is based on daily data from the constituents of the STOXX Europe 600 index, covering the period 2010-2024. Portfolios are constructed annually by ranking stocks into volatility groups, and a range of moving average portfolios (MAPs) with different signal lengths are tested against both a passive buy-and-hold benchmark and the CAPM. The results show that abnormal returns are concentrated in the most volatile portfolios, particularly when shorter moving averages are employed. These findings are broadly consistent with Han et al. (2013), who document similar effects in the U.S. market. Moreover, recent empirical work in emerging markets echoes the central mechanisms of this dissertation. For instance, Mahajan et al. (2025) analyse the NIFTY 50 index over the period 2010-2023 and find that both simple and exponential moving averages provide valuable trend signals, especially under different market regimes. This reinforces the view that moving average strategies retain predictive power across distinct equity markets and geographical contexts.

Although often criticised, technical analysis remains widely used among investors. Surveys report that around 90% of foreign exchange traders in the UK (Taylor and Allen, 1992), more than 80% of fund managers in Germany (Menkhoff, 2010), and a large share of institutional investors worldwide (Park and Irwin, 2007) incorporate technical indicators into their trading decisions. More recent evidence suggests that technical analysis retains predictive power in developed markets such as the U.S. and Europe (Menkhoff and Taylor, 2007; Neely et al., 2009). This underlines the relevance of assessing the profitability of systematic rules in the European context.

From an intuitive perspective, conditioning investment strategies on volatility is meaningful because more volatile stocks generate larger price swings and stronger technical signals, thereby increasing the potential effectiveness of moving average rules. Conversely, less volatile stocks tend to follow more stable patterns, where such strategies add little value. This rationale is supported by studies linking volatility to mispricing and return predictability (Ang et al., 2006; Jiang et al., 2009). Building on this, Moreira and Muir (2020) provide new evidence that volatility-managed portfolios remain effective even under periods of market stress in developed markets. Their findings strengthen the case that conditioning strategies on volatility can systematically enhance performance.

This dissertation fills a gap in the academic literature on the European stock market by examining the “new anomaly” documented by Han et al. (2013), applied here to the constituents of the

STOXX Europe 600 index. Despite the controversy surrounding technical analysis, it continues to be widely employed by investors and brokerage firms (Covel, 2017), whose advice often relies on a combination of recent news and some of the most widely used technical indicators. This makes the subject particularly relevant for both academics and practitioners.

Therefore, this study contributes to the academic debate on the persistence of technical trading anomalies in developed markets and provides potential practical insights for investors seeking systematic strategies that adapt to volatility conditions. While limited to the European equity market and the 2010-2024 period, its findings may offer indications regarding the broader applicability of volatility-conditioned trend-following rules.

The remainder of this dissertation is structured as follows. Chapter 2 reviews the relevant literature on moving average strategies, market timing, and the relationship between volatility and return predictability. Chapter 3 describes the data sources, portfolio construction, and methodological framework, building upon Han et al. (2013). Chapter 4 presents the main empirical results by comparing buy-and-hold and moving average strategies across volatility deciles and evaluating their performance in terms of risk-adjusted returns and CAPM alphas. Chapter 5 conducts a set of robustness tests to verify that the findings are not driven by methodological choices or sample-specific characteristics. These include alternative moving average horizons, break-even transaction cost estimates, and sub-period analyses, which together reinforce the credibility and practical relevance of the results. Finally, Chapter 6 concludes by summarising the key findings, discussing their theoretical and practical implications, and suggesting directions for future research.

# 2. Literature Review

The current study relies on European stock market data to test the hypothesis that a trading strategy based on moving averages timing can generate significant abnormal returns when compared to the traditional models. To prepare the ground for the empirical study, a deeper analysis of the existing literature is detailed in the current chapter, beginning with an overview of Technical Analysis and followed by a discussion of related studies.

Technical trading strategies have long attracted academic interest for their potential to generate excess returns through systematic rules. Among them, moving average (MA) rules are particularly popular due to their simplicity and empirical performance. Brock et al. (1992) were among the first to rigorously test MA-based strategies, finding that both simple and exponential moving averages displayed statistically significant predictive power over stock market returns. Their work provided early support for the idea that technical indicators may capture behavioural biases or slow information diffusion in prices. Subsequent studies, such as Neely et al. (2014), confirmed the profitability of moving average timing across international markets, although performance often depends on the sample period and market conditions.

Another important dimension is the role of volatility in return predictability. While traditional finance theory, particularly the Capital Asset Pricing Model (CAPM), posits a positive relationship between risk and expected return, empirical evidence has been mixed. Ang et al. (2006) document a "low-volatility anomaly" whereby high-volatility stocks tend to earn lower returns than their low-volatility counterparts. Moreira and Muir (2017) further show that volatility timing - adjusting exposure based on forecasted volatility - can improve portfolio performance. These findings challenge the standard view of risk premiums and suggest that volatility itself may carry informational content exploitable through timing rules.

Han et al. (2013) bridge both strands of literature by examining whether a simple moving average strategy, applied to portfolios sorted by volatility, can generate abnormal returns. Their study, based on U.S. equities, shows that a 10-day MA rule is particularly effective in high-volatility portfolios, delivering significant CAPM alphas. The returns persist even after controlling for size, value, momentum and short-term reversal factors, suggesting the anomaly cannot be explained by traditional asset pricing models. While their focus is restricted to the U.S. market, their findings offer strong support for the use of volatility-sensitive timing strategies. Also, their results raise some questions about the assumptions behind traditional financial theory. If a simple timing rule like a moving average can generate consistent abnormal returns - especially in high-volatility portfolios - this contradicts what the Efficient Market Hypothesis would predict, at least in its weak form. It also challenges the CAPM's idea that risk and return move together linearly. The fact that volatility itself seems to carry useful information for timing strategies suggests that markets might not fully price in short-term risks, or that behavioural factors may still play a role. This opens the door for technical signals to be more than just trading noise - they might, in fact, reveal real inefficiencies.

This dissertation contributes to the existing literature by extending Han et al. (2013) in two key aspects: first, by applying the MA strategy to European stock portfolios sorted by volatility; and second, by systematically testing a broader range of moving average lengths (5, 10, 20, 50, 100 and 200 days). This broader approach allows for an assessment of how the timing signal's responsiveness interacts with portfolio volatility and whether the anomaly is robust across markets and time horizons.

The first segment of this chapter includes an analysis on the field of technical analysis, its origins and success according to multiple authors who studied this topic. In the second part, a closer focus is given to studies relying on moving averages timing strategies, with a particular emphasis on the stock market. In the third, some of the most relevant studies on stock market volatility are analysed, building the necessary foundation to later advance to the empirical study. In the fourth and final part, the existing literature that combines volatility with technical trading rules is reviewed, highlighting the research gap that this dissertation seeks to address.

## 2.1. Research on Technical Analysis

When developing a trading strategy, two main methodologies may be applied, each with its distinct underlying assumptions. On one hand, performing a fundamental analysis requires a set of assumptions that ultimately allow us to estimate the cash flows that should be generated by such an asset to its owner/holder, and consequently its value. Such exercise requires a particular expertise from the valuer on such type of assets to be able to establish adequate cash-flow projections, which are later discounted to their present value generally using a classic model such as the Capital Asset Pricing Model (CAPM) or the Fama-French 3-factor model.

On the other hand, technical analysis tends to be applied to every tradable asset (assuming a minimum level of liquidity), as it relies mostly on the study of price and volume behaviour to develop indicators and trading strategies (Murphy, 1999; Pring, 2002). Technical analysis is rooted in the Dow Theory, with early contributions by Hamilton (1922) and Rhea (1932), and four main assumptions are typically derived from it:

- i.Averages discount everything;
- ii. Stock prices are determined by the interaction of market demand and supply;
- iii. Stock prices tend to move in trends;
- iv. History tends to repeat itself.

To start, technical analysis has an implicit assumption that averages discount everything, in a sense that prices incorporate all characteristics from supply and demand. Another fundamental assumption is that prices tend to move in trends, meaning that technical analysts might be able to identify such patterns and potentially increase their possibilities of trading successfully (which, according to the EMH, should not be able to occur consistently as prices tend to move following a random walk, i.e. not in a predictable way, under the weak form of efficiency).

However, this does not imply that traders can identify such strategies with perfect accuracy, because the way supply and demand react to new information is still widely uncertain and sometimes does not respect what would be expected in theory.

Despite its rejection among a large portion of traditional academics, technical analysis has been increasingly used by many retail and professional investors. And, as a larger portion of the supply or demand for a particular security uses the same price analysis, it creates a self-fulfilling phenomenon that can have a significant impact in the market as a whole, especially when considering the magnitude of algorithm trading.

The relevance of technical analysis among traders and investors is not particularly recent. For example, Schwager (2012), in is famous book, interviews some reputable traders of the time, which claimed the importance of price analysis in building a profitable strategy.

But in the foundation of technical analysis lies the Dow Theory, first introduced by Charles Dow during the 19th century. In 1882, Charles Dow and a reporter named Edward Jones decided to start the Dow, Jones & Company (currently still in activity) dedicated to deliver unbiased information to the trading community. The Dow Jones Industrial Average was gradually built through the publications created, which started to present the price movement of certain stocks in the shipping and rail industry, and authors decided to include the average values to allow the reader to quickly get a notion of how the market as a whole was behaving.

Having died in 1902, Charles Dow was incapable of publishing his complete theory, but several associates have developed his work further and introduced it within the community of traders. Some contributions can be attributed to Hamilton (1922) and Rhea (1932), who provided important developments in the formulation and dissemination of Dow Theory.

Since its introduction, technical analysis practitioners have developed other indicators and strategies, but the insights given by the Dow Theory are still in its foundation. Studies on technical analysis are nowadays available in large numbers, but conclusions may not always support or reject its effectiveness.

Studies around this topic have surged mostly after the work from Fama and Blume (1966) where the authors test the random walk hypothesis in stock market prices, more precisely to compare the robustness of different statistical procedures, finding that both standard procedures and the widely used at the time Alexandrian filter rules showed similar conclusions in favour to the random walk hypothesis.

A large number of subsequent studies have approached the topic by creating a set of trading rules and applying these to the most relevant market indices. For example, Brock et al. (1992) tests two of the most popular trading strategies (not only at that time, but still today, probably due to their simplicity), the moving averages and trading range breakouts. Using data from the Dow Jones Index from 1897 to 1986, the authors find evidence suggesting support for these strategies, defying the random walk hypothesis and other correlation models as well. In addition, authors found that buying signals tended to be more consistent and generated higher returns, whereas returns following selling signals tended to be negative.

More recently, Marshall et al. (2009) tested these same trading strategies, moving averages and trading range breakouts, and their profitability within a set of U.S. stocks, in function of liquidity, size, and industry characteristics. And, despite finding that during the period from 1990 to 2004 these strategies were not typically profitable, after this year, evidence suggests that a profit could be generated, especially for stocks with less volume and for companies with lower market capitalization. Regarding the industry, authors found no significant bias but realized that when a strategy is capable of generating statistically significant abnormal returns these show to be higher if longer timeframes are used for the decision.

However, going back to the study by Brock et al. (1992), it is important to note that the authors did not consider transaction costs when comparing the trading rules versus a buy-and-hold strategy. Bessembinder and Chan (1998) replicate the work previously made, this time including transaction costs, finding that these indeed reduced the significance of the findings in support of the trading rules that have been affirmed, and that results were not necessarily inconsistent with the market efficiency hypothesis.

In fact, several studies that have based their research in the same moving average and trading range breakout strategies considered by Brock et al. (1992) have found similar conclusions, according to which the frequency required to trade such strategies led to significant transaction costs that would erase any abnormal profit initially generated. This is the example of Coutts and Cheung (2000), which study the Hang Seng index of the Hong Kong Stock Exchange for the period 1985-1997, and find that although the trading range breakout rule presented as the strongest strategy, it was still incapable of generating positive abnormal returns if net of transaction costs and associated opportunity costs. A similar study was performed by Hudson et al. (1996) where authors studied a larger timeframe ranging from year 1935 to 1994, and found that for the UK stock market technical trading rules showed again to have some predictability power, but were unable to generate consistent profits above trading costs.

Nevertheless, it is important to note that technical analysis and related trading strategies are widely used not only by retail investors, but professionals as well. For instance, Menkhoff (2010) analysed survey evidence of 692 fund managers from five countries, and when asked on how important technical analysis was to develop their strategies, about 86% rely on it and 20% even said to prefer this methodology over fundamental analysis and flows (such as order flow and observed transactions). A previous study from Lease et al. (1974) shows that the importance of technical analysis was already relevant among individual investors, as 27% of the inquired claimed to use this methodology. Hoffmann and Shefrin (2014) reached a similar figure in their study, having concluded that 32% of investors inquired used technical analysis either in exclusivity or as a complement to another methodology. Counting only those who use technical analysis in exclusivity, it is also possible to contrast the percentage of 9% obtained in the latter study with approximately 4% in the study by Lease et al. (1974).

Overall, literature covering the effectiveness and profitability of technical analysis is vast, with authors applying multiple trading rules to different markets in order to test both their efficiency or capacity to generate abnormal returns. Menkhoff and Taylor (2007) presents a quite extensive review on the research developed until the time of writing, particularly over the foreign exchange market. In a first moment, authors conclude that in fact technical analysis truly had an important role in the decision process of market participants, arguing that this should not be explained by a sort of herd irrationality. But it is noted as well that the profitability of technical analysis could be also associated with government interventions over the exchange rate, as decisions made tend to generate large movements. In addition, authors revealed that technical analysis showed to help decision makers in finding non-fundamental price factors, with particular importance in the short term.

A comprehensive literature review was performed as well by Park and Irwin (2007). In their study, authors reviewed a total of 137 academic papers on technical analysis covering the period from 1960 to 2004, dividing the literature in two main categories – the early studies (from 1960 to 1988) and the modern studies (from 1988 onwards), starting with Lukac et al. (1988). From this research, the authors found in a first moment that early studies showed mostly support to the hypothesis that technical analysis was profitable for both foreign exchange market and futures markets, but not for the equity market. On the other hand, most modern studies suggest instead that technical analysis is also profitable for the equity market, being able to generate abnormal returns at least until the end of 1980s. From the total 95 modern studies, 56 revealed evidence in support of technical trading rules' profitability, whereas 20 displayed insignificant evidence and 19 presented mixed conclusions. Their findings suggest that technical strategies can be effective under specific market conditions.

Overall, while technical analysis remains controversial in academic circles, empirical evidence suggests that under certain conditions - such as high volatility, low liquidity, or limited information - it may provide traders with a profitable edge. This justifies its continued study, particularly when applied systematically and with appropriate risk management.

## 2.2. Research on Moving Average Timing Strategies

Although technical analysts base their strategy on two main indicators – price and volume – there are several indicators built upon these, in order to assess the strength of the price movement, likelihood of a trend reversal, among others. And research does test several trading rules, including (1) filter rules (which generate buying or selling signals depending on whether the stock price increased or decreased by a certain percentage compared to a previous low or high, respectively) – such as the study by Fama and Blume (1966) – (2) relative strength rules (which examine the strength of a share price movement and compare it to the market as a whole) – studied by authors such as Levy (1967), Akemann and Keller (1977), Bohan (1981), Brush and Boles (1983), Jacobs and Levy (1988) and (3) moving average trading rules, which is the methodology examined in this study.

A moving average corresponds to an average of the prices of $n$ previous trading sessions. For example, a 10-day moving average corresponds to the average of the prices from the previous ten days, where when a new price is available the last observation is replaced by it. There are some variants to this moving average, where two of the most used are the simple moving average (which corresponds to the simple arithmetic average) and the exponential moving average (which introduces a factor that gives higher weight to the most recent prices, therefore making this indicator more reactive to the current market movement).

One of the main purposes of using moving averages within a trading strategy relies on the capacity to reduce the price noise and better acknowledge its trend. Additionally, technical analysts often build trading systems with two or more moving averages with different lengths, assessing this way both short and long-term trends, and how these are evolving according to each other.

Moving average rules have been interpreted in the literature either as mean-reversion signals or as indicators of support and resistance levels. Brock et al. (1992) provide early evidence that simple moving average rules can generate statistically significant returns in U.S. equity markets. More recently, Han et al. (2013) show that the profitability of such strategies is linked to volatility, with stronger results in high-volatility stocks. These findings suggest that technical trading rules may exploit persistent patterns in price dynamics that are not fully consistent with the weak form of the Efficient Market Hypothesis.

Research around the effectiveness of moving average trading strategies and its capacity to generate abnormal returns when compared to a buy-and-hold strategy is already vast, but often contradictory.

Starting with the section of studies finding no statistical support for the capacity of moving average trading strategies to generate abnormal returns, the previous chapter introduced the work by Brock et al. (1992), and the subsequent study by Bessembinder and Chan (1998) built upon the former, which revealed the importance of considering trading costs within the analysis, as it could explain large part of the abnormal returns that were identified by the former study when implementing trading strategies based on moving averages and trading range breakouts.

Another similar chain of conclusions started with the study by Glabadanidis (2015), where the author presents evidence suggesting that a strategy based on moving averages could generate not only higher average returns but a lower variance as well, when compared to a buy-and-hold strategy. The author used an extremely broad database, including monthly returns of USA decile portfolios sorted by book-to-market ratio, market size and momentum, data from seven international markets, and 18,000 individual USA stocks. Conclusions point to an excess risk-adjusted return between 3% and 7% per year, after transaction costs, with this performance being mostly explained by the volatility of stock returns, as well as some macroeconomic inputs. However, Zakamulin (2018) in a following study that built upon the former conclusions, it was found that these abnormal returns were associated with the simulated trading approach subject to look-ahead bias. But once the authors removed this look-ahead bias out of the equation, conclusions indicated that the moving average trading strategy was only marginally better than the benchmark buy-and-hold strategy, without statistical evidence suggesting that the former was capable of generating consistent abnormal returns.

Performing a study in the European stock market, Metghalchi et al. (2012) concluded that, for the 16 stock markets studied for the period between 1990 and 2006, there was statistical evidence in support of moving averages and their prediction capacity, by facilitating the identification of recurring price patterns that led to abnormal returns, even after considering transaction costs. To perform their study, authors based their method on White's (2000) Reality Check test, which measures the impact of data snooping bias (i.e. a statistical bias which consists in the practice of performing multiple combinations of explanatory variables in order to attain a specific result) and adjusts its effect.

Other markets have already been studied as well. For instance, Gunasekarage and Power (2001) study the performance of moving average trading rules in four emerging South Asian stock markets, with findings indicating that this trading rule generated predictability ability and led to higher returns once compared with a buy-and-hold strategy.

Beyond equity markets, Zhou et al. (2021) analyse carbon emission markets and show that moving average strategies retain predictive power even in relatively young and less liquid settings. Their results highlight the robustness of trend-following rules across different asset classes and institutional contexts.

Going back to the study by Han et al. (2013) authors have applied the moving average timing strategy to CRSP[1] NYSE/AMEX volatility decile portfolios, calculating the 10-day average prices of these. Afterwards, for each portfolio, authors have defined the trading rules as follows: decision to buy or hold the portfolio if the price of the previous day is above the 10-day moving average; invest the money in a 30-day T-bill (used as a proxy for a risk-free asset) if the opposite happens. Comparing these results with a traditional buy-and-hold strategy, authors found evidence suggesting that this strategy was able to generate higher returns and this differential increased with the volatility of the respective portfolio, ranging from 8.42% to 18.70% per annum. Using the capital asset pricing model (CAPM) as another reference to estimate the risk-adjusted returns, it is also found that abnormal returns were generated by the portfolios in an ascending order (except for the highest decile portfolio), ranging from 9.31% to 21.76% on an annual basis. Similar conclusions were obtained when using the Fama and French (1993) risk-adjusted returns.

To assess the robustness of the results, Han et al. (2013) have performed the same exercise for different moving average lengths, namely 20, 50, 100 and 200 days. This led to the finding that abnormal returns were still detected but presented more relevant for shorter MA lengths. For a MA length of 20 days abnormal returns were found to range between 7.93% to 20.78%, while for longer periods this was much lower but in most cases over 5% calculated on an annual basis. Due to the impact that transaction costs have shown to have when testing the profitability of technical trading rules, authors have also studied the resulting trading behaviour and determined the break-even transaction cost. Conclusions have led to a relatively small impact of transaction

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[1] Center for Research in Security Prices.

costs, as the break-even was relatively large and the moving average timing strategy did not generate too many trading signals.

In their study, Han et al. (2013) went further and tried to deepen the knowledge on the abnormal returns generated by the moving average timing strategy compared to the buy-and-hold profile. Among other tests, authors started by analysing if the strategy had the capacity to time the market, and if abnormal returns persisted if this factor was controlled, finding that in fact there is some predictability power associated to a moving average trading strategy, but that abnormal returns persisted even after disregarding this.

Despite the diversity of findings, the literature suggests that moving average rules can provide useful signals under certain market conditions, particularly in environments marked by volatility or inefficiencies. The diversity of findings highlights the importance of the dataset, period, and methodology chosen, and supports further testing with more recent data.

## 2.3. Stock Market Volatility

The scope of this study is the analysis of moving average trading rules and their capability of generating abnormal returns, connecting this to the volatility of the portfolio studied to assess if the former tends to generate higher or lower predictability power. Han et al. (2013) show that the predictive power of moving average rules is strongest in high-volatility portfolios, suggesting that greater information uncertainty makes such timing strategies more effective. More recently, Mahajan et al. (2025) apply a similar framework to the Indian stock market, showing that moving average rules also generate abnormal returns in high-volatility portfolios. Their findings reinforce the idea that volatility amplifies the predictive power of technical strategies across different geographical settings.

Moving averages constitute what is known as a trend-following strategy, meaning that the success of this trading rule depends upon the capacity of discovering trends on price movements that persist for a determined period. This can be associated with the price underreaction, and according to Zhang (2006) this was the explanatory cause for stock price continuation, as investors underreacted to public information, particularly more when in case of higher information uncertainty. This study is built on this line of thought, using portfolios sorted by volatility as a proxy for different levels of information uncertainty.

Marshall et al. (2009) find that technical trading rules, including moving averages, are more effective in stocks with higher volatility and lower liquidity. This supports the idea that price inefficiencies are more common in less stable stocks, where timing strategies can better exploit short-term trends. Similarly, Han et al. (2013) show that a 10-day moving average rule results in significantly higher abnormal returns in high-volatility portfolios, confirming that volatility can enhance the effectiveness of trend-based signals.

Beyond moving average strategies, other approaches have examined the advantages of adjusting investment exposure based on volatility itself. Moreira and Muir (2017) proposed a different approach to portfolio management by modifying exposure according to expected volatility. Instead of holding fixed allocations their strategy decreases exposure during high-volatility periods and boosts it when markets are calmer. This straightforward rule yields higher Sharpe ratios than static portfolios and performs well across various asset classes. Their findings challenge the traditional view that higher risk should lead to higher returns, showing that managing exposure dynamically can improve performance.

Relatedly, Rombouts et al. (2014), who explore the role of volatility forecasting in portfolio allocation. They show that improving volatility forecasts can lead to better decisions on portfolio construction, especially when risk varies over time. While they focus on econometric models and not specifically on moving average timing strategies, their findings support the broader idea that reacting to volatility - as moving average strategies implicitly do – can enhance performance.

## 2.4. Behavioural Biases and the Underreaction Hypothesis

Beyond traditional market efficiency frameworks, behavioural finance provides explanations for why technical trading rules may remain profitable. The market underreaction hypothesis suggests that investors tend to adjust their beliefs too slowly to new information, leading to gradual rather than immediate price changes. This inertia gives rise to predictable return patterns, particularly short- to medium-term momentum, which technical strategies can exploit.

Key contributions include Barberis et al. (1998), who show that investors display conservatism by underweighting recent news, Daniel et al. (1998), who emphasise the role of overconfidence and biased self-attribution, and Hong and Stein (1999), who argue that information diffuses slowly across heterogeneous agents. These frictions become more pronounced under high volatility, when uncertainty exacerbates disagreement and delays price adjustments.

Empirical evidence supports these mechanisms: Jegadeesh and Titman (1993, 2001) document persistent momentum effects, while Han et al. (2013) confirm that MA rules yield abnormal returns in high-volatility portfolios. This suggests that volatility may also capture systematic behavioural mispricing.

These results also resonate with Harvey et al. (2022), who argue that traditional asset pricing models systematically fail to account for persistent cross-sectional anomalies. From this perspective, the abnormal returns generated by volatility-conditioned moving average strategies may be viewed as part of a wider challenge to risk-based explanations in modern asset pricing.

Overall, the literature suggests that moving average strategies can generate abnormal returns under certain conditions, but evidence for European equities remains limited.

This dissertation seeks to fill this gap by systematically testing volatility-conditioned moving average strategies in the European market.

# 3. Research Questions and Methodology

## 3.1. Database

Building on the literature reviewed in the previous chapter, an empirical study was developed to test the central hypothesis of this dissertation. To do so, data were obtained from LSEG Workspace (formerly Refinitiv), including daily index prices and returns for a set of European decile portfolios divided into ten groups (deciles) based on their annual standard deviation, measured as the annualised standard deviation of daily returns from the previous year. Once each stock was assigned to one of the 10 decile portfolios, the portfolios' average price and daily returns were calculated, assuming equal weight for each stock and an annual rebalancing at year-end. Data was collected over a 15-year timeframe, covering the period from January 2010 to December 2024, comprising 3,907 daily observations. These include the daily closing prices of all components of the STOXX Europe 600 index. Each decile portfolio had an average of 60 constituents, while the index itself had an average of 600 constituents. In order to mitigate survivorship bias, all firms that were part of the index at any point during the sample period were included, even if they were later delisted. Portfolio composition was updated annually to reflect index changes.

## 3.2. Methodology and Hypotheses

The hypothesis proposed by this study, in line with Han et al. (2013), is to analyse whether a moving average timing strategy applied to volatility portfolios of European stocks can generate higher returns than a simple buy-and-hold strategy, as well as abnormal returns when compared to a valuation model: specifically, the capital asset pricing model (CAPM).

In this dissertation, moving average timing rules are implemented to generate buy and sell signals. Two main rationales underlie these rules: (i) a mean-reversion perspective, where deviations of short-term prices from longer-term averages are expected to converge; and (ii) the interpretation of moving averages as dynamic levels of support and resistance, widely used in technical analysis (Murphy, 1999; Pring, 2002). A typical buy signal occurs when prices break above a moving average and subsequently find support at that level, under the assumption that trends persist and upward momentum is likely to continue.

Additionally, it is determined if this effect is more pronounced in assets or portfolios with higher volatility, as these are more likely to produce greater levels of information uncertainty, which may lead to price underreaction and cause investors to favour technical analysis over fundamentals. Therefore, one of the main components of this study is the definition of a moving average, which is used as a trading signal by calculating this level for a determined length and contrasting it with the recent price level. For a $n$-day period moving average, defining $R_{it}$ as the returns of each decile portfolio $i$ for a particular day $t$, and $P_{it}$ the corresponding daily portfolio price, the moving average (MA) at a particular day $t$ with lag $n$ periods is defined as follows:

$$MA_{it} = \frac{P_{it} + P_{i(t-1)} + P_{i(t-2)} \dots + P_{i(t-(n-1))}}{n}$$

Following a similar approach as Han et al. (2013), the hypothesis is tested for multiple timeframes $L$, including 5, 10, 20, 50, 100 and 200-days moving average, corresponding to the most used lengths by investors.

The trading strategy is structured as follows. On each trading day $t$ for portfolio $i$, the last closing price $P_{t-1}$ is compared with the moving average price $A_{t-1}$. If the former is above the latter, then the decision is to invest (or remain invested) in the respective decile portfolio, whereas if the closing price of the decile portfolio is equal or below the respective moving average, the investment is transferred to the Germany 3-months Government Bond Yield – $r_{ft}$. Notice that this trading strategy provides signals with a lag of one day. Therefore, assuming that prices evolve in cycles and trends, the rationale of this trading strategy is to be invested during positive trends and exit once it shows signs of changing. It is not considered the possibility of short selling during downtrends (i.e. when price of a decile portfolio would close below its respective moving average) to ensure consistency and comparability with similar studies.

The returns obtained by a $L$-days moving average trading strategy are thus expressed as follows:

$$\tilde{R}_{it,L} = \begin{cases} R_{it}, & if\ P_{i(t-1)} > A_{i(t-1),L} \\ r_{ft}, & otherwise \end{cases}$$

It is important to note that, during the sample period, European risk-free rates occasionally turned negative. In such cases, holding the risk-free asset would effectively imply a guaranteed nominal loss, which challenges the traditional assumption that investors always have access to a strictly positive risk-free return. While the CAPM framework requires the inclusion of a risk-free benchmark for theoretical consistency, these episodes highlight the practical limitations of the model and reinforce the relevance of evaluating active timing strategies as alternatives to remaining invested in assets with negative yields.

Following similar studies, the performance of the moving average trading strategy is compared relatively to a buy-and-hold strategy of the respective decile portfolio. Using a similar nomenclature as Han et al. (2013), this excess return is defined as the return on the moving average portfolio (MAP), and for each decile portfolio $i$ can be obtained as follows:

$$MAP_{it,L} = \tilde{R}_{it,L} - R_{it}\ ,\ i = 1, \ldots, 10$$

Afterwards, this difference is examined and results compared for different moving average lengths and between decile portfolios. The moving average trading rule displays evidence of being successful in generating higher returns if $\tilde{R}_{it,L} > R_{it}$.

One important concern surrounding studies on trading rules is associated with the frequency of the signals, which generate real life transaction costs. Using this moving average strategy, buying or selling signals can occur at a daily frequency, therefore it is important to study how many trades it would have to be done in order to obtain the expected returns, and if the transaction costs incurred in the meantime do not cannibalize all the abnormal returns eventually identified. Using data from the STOXX Europe 600 constituents, covering the period from years 2010 to 2024, in this study trading frequency is analysed, and the findings are summarised in a table reporting the moving average lengths and the ten volatility decile portfolios. For each, the average holding period of trading signals is analysed, corresponding to the average interval that prices take to cross upward or below the respective moving average and generate a change in the investment decision. In accordance with Han et al. (2013), it is expected that trading based on longer moving average lengths have an average holding period significantly higher than when using shorter lengths, as the former moving average tends to be less reactive to recent prices. Similarly, portfolios with less volatility are expected to generate less trading signals and consequently higher holding periods than portfolios with higher levels of volatility (where prices are more likely to cross their respective moving average).

Up to this point, transaction costs have still not been included into the return's comparison. In accordance with what was concluded from our literature review, some studies suggest that evidence of abnormal returns generated by trading rules like the moving average may vanish once transaction costs are taken into account. But determining what is the correct level of transaction costs tends to be relatively hard, and opinions may differ.

In resemblance to the studies made by Balduzzi and Lynch (1999), Lynch and Balduzzi (2000) and Y. Han (2006), it is assumed that one would incur transaction costs only when trading the decile portfolios, where no cost is considered when trading the risk-free asset. Going back to our previous formula, and considering a transaction cost τ per trade, the return generated from the moving average trading strategy are now detailed as follows:

$$\tilde{R}_{it,L} = \begin{cases} R_{it} \quad , & if\ P_{i(t-1)} > A_{i(t-1),L}\ and\ P_{i(t-2)} > A_{i(t-2),L} \\ R_{it} - \tau, & if\ P_{i(t-1)} > A_{i(t-1),L}\ and\ P_{i(t-2)} < A_{i(t-2),L} \\ r_{ft} \quad , & if\ P_{i(t-1)} < A_{i(t-1),L}\ and\ P_{i(t-2)} < A_{i(t-2),L} \\ r_{ft} - \tau, & if\ P_{i(t-1)} < A_{i(t-1),L}\ and\ P_{i(t-2)} > A_{i(t-2),L} \end{cases}$$

In other words, for each decile portfolio $i$, when price crosses the moving average upward or downward, it generates a buying or a selling signal, respectively, and a transaction cost must be considered. Otherwise, during the holding period, the return corresponds to the return of the asset being held, without any additional penalty.

Rather than assuming an arbitrary level for transaction cost τ, this study focuses on computing the break-even transaction cost that would fully offset the abnormal returns of the strategy.

This break-even transaction cost is obtained by identifying the level of trading frictions at which the alpha of the strategy becomes statistically indistinguishable from zero. In other words, it represents the maximum cost per trade that an investor could incur while still capturing abnormal returns from the moving average strategy. By adopting this approach, the analysis provides a more realistic assessment of the economic significance of the results, as it explicitly accounts for market frictions rather than assuming frictionless trading conditions.

The break-even transaction cost, denoted below as $\tau^*_i$, represents the maximum cost per trade that can be incurred without eliminating the abnormal return of the moving average strategy. Formally, $\alpha_i$ corresponds to the estimated abnormal return (before costs) of portfolio i, while $N_i$ is the average number of trades executed in that portfolio. Thus, the break-even cost is computed as the ratio between the abnormal return and the trading frequency. If market transaction costs exceed this threshold, the strategy ceases to be economically viable, even if statistical significance is preserved.

$$\tau^*{}_i = \frac{\alpha_i}{N_i}$$

This framework allows the subsequent empirical analysis to assess not only whether abnormal returns exist, but also whether they remain economically relevant once transaction costs are realistically accounted for.

# 4. Empirical Results

Using data covering the period from 2010 to 2024 for the STOXX Europe 600 index constituents, this section first presents the summary statistics of the volatility decile portfolios, the MA timing portfolios and the respective MAPs for the different moving average lengths considered - 5, 10, 20, 50, 100 and 200 days. Afterwards, it is also studied the profitability of the MAPs regarding the abnormal returns, using the CAPM and the STOXX Europe 600 index and German three-month Government Bond Yield (DE3MT=RR) as inputs in the estimation of the equity risk premium. An analysis is also made regarding the average holding period, trading frequency, and the break-even transaction costs (BETC). Lastly, possible explanations for the profitability of the MAPs strategy are explored, based on existing literature.

## 4.1. Summary Statistics

Table 1 below presents the summary statistics of returns for three portfolio strategies: the buy-and-hold volatility decile portfolios (Panel A), the 10-day moving average timing portfolios (Panel B), and the moving average position portfolios (MAPs, Panel C). For each portfolio, the annualised average return, standard deviation, skewness, and Sharpe ratio are reported. Additionally, the last column of Panel C shows the success rate of the MA timing strategy.

# Table 1 - Summary Statistics MA (10)

| | Panel A | | | | Panel B | | | | Panel C | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Volatility Decile Portfolios | | | | MA (10) Timing Portfolios | | | | MAP | | | |
| **Rank** | **Avg. Ret.** | **Std. Dev.** | **Skew** | **SRatio** | **Avg. Ret.** | **Std. Dev.** | **Skew** | **SRatio** | **Avg. Ret.** | **Std. Dev.** | **Skew** | **Success** |
| **Low** | **11.31%** | 29.34% | -1.92 | 0.3515 | **24.76%** | 12.47% | 0.04 | 1.9058 | **13.45%** | 25.77% | 2.51 | **61.43%** |
| **2** | **13.22%** | 13.95% | 0.26 | 0.87.59 | **23.97%** | 9.67% | 0.41 | 2.3748 | **10.75%** | 16.18% | 0.29 | **62.02%** |
| **3** | **17.58%** | 19.51% | -1.12 | 0.8495 | **28.40%** | 7.32% | -0.11 | 3.7447 | **10.83%** | 18.20% | 0.63 | **59.72%** |
| **4** | **14.81%** | 20.59% | 0.64 | 0.6706 | **34.11%** | 14.22% | 0.97 | 2.3285 | **19.30%** | 21.47% | 0.29 | **62.07%** |
| **5** | **13.59%** | 22.33% | 0.57 | 0.5638 | **29.83%** | 8.37% | -0.84 | 3.4437 | **16.23%** | 21.37% | -0.33 | **60.97%** |
| **6** | **12.07%** | 28.48% | 1.52 | 0.3886 | **36.02%** | 12.79% | 0.30 | 2.7376 | **23.95%** | 22.97% | -0.41 | **62.27%** |
| **7** | **6.43%** | 28.87% | 0.72 | 0.1880 | **32.63%** | 19.86% | 0.54 | 1.5929 | **26.21%** | 25.07% | 0.96 | **60.43%** |
| **8** | **0.22%** | 60.95% | 2.04 | -0.129 | **36.72%** | 15.91% | 2.18 | 2.2447 | **36.50%** | 49.84% | -1.12 | **59.84%** |
| **9** | **-8.31%** | 20.13% | 0.15 | -0.4625 | **34.66%** | 16.23% | 0.19 | 2.0732 | **42.97%** | 24.87% | 1.17 | **59.12%** |
| **High** | **-36.17%** | 47.25% | 1.09 | -0.7866 | **40.87%** | 27.32% | 0.90 | 1.4590 | **77.03%** | 44.32% | -1.02 | **57.31%** |
| **High - Low** | **-47.48%** | 17.91% | 3.01 | -0.1138 | **16.10%** | 14.85% | 0.86 | -0.4468 | **63.58%** | 18.55% | -3.53 | **-4.12%** |

This table reports annualised summary statistics for three portfolio strategies: (i) buy-and-hold volatility decile portfolios (Panel A), (ii) 10-day moving average (MA) timing portfolios (Panel B), and (iii) Moving Average Portfolios (MAPs), defined as the difference between the MA timing and buy-and-hold returns (Panel C). For each decile, the average return, standard deviation, skewness, and Sharpe ratio are shown, along with the success rate of MAPs. Portfolios are constructed from STOXX Europe 600 constituents, sorted annually into deciles by the prior year’ s daily return volatility. The sample covers January 2010 to December 2024, and all results are presented in annualised terms.

Panel A indicates that the average returns of buy-and-hold portfolios do not exhibit a clear monotonic pattern with volatility deciles. While lower-volatility portfolios generate positive returns (e.g., 11.31% for decile 1), the highest-volatility decile yields strongly negative returns (-36.17%). The High-minus-Low volatility spread delivers a strongly negative annual return of -47.48%, with Sharpe ratios turning negative in the higher-volatility portfolios. This highlights the underperformance of high-volatility stocks relative to their low-volatility counterparts.

In contrast, Panel B shows that the MA timing strategy consistently delivers higher returns with significantly lower volatility. Average annual returns range from 23.97% to 40.87% across deciles, with standard deviations roughly 65% lower than their buy-and-hold counterparts. As a result, Sharpe ratios are much higher, exceeding 3 in some mid-volatility portfolios. Additionally, skewness is generally less negative or even positive, indicating better return distributions.

Panel C illustrates the incremental performance of the MA strategy compared to the buy-and-hold benchmark. Instead of representing a separate trading approach, this panel breaks down the effect of timing itself. The values for return, skewness, and Sharpe ratio reflect the marginal impact of applying the MA rule. MAP returns grow with volatility deciles, reaching a peak of 77.03% in the highest decile, while volatility remains moderate. Notably, the skewness remains consistently positive across deciles, confirming the asymmetry in return distributions caused by timing. The final column shows the strategy's success rate, defined as the proportion of days when the MA signal accurately predicted market direction, meaning out of the market on negative returns days and invested on days with positive returns. Although the success rate varies across deciles, Han et al. (2013) suggested a raw accuracy around 60% and this study around 61%, supporting the presence of consistent timing skill.

**Figure 1 - Annualised average returns MA (10)**

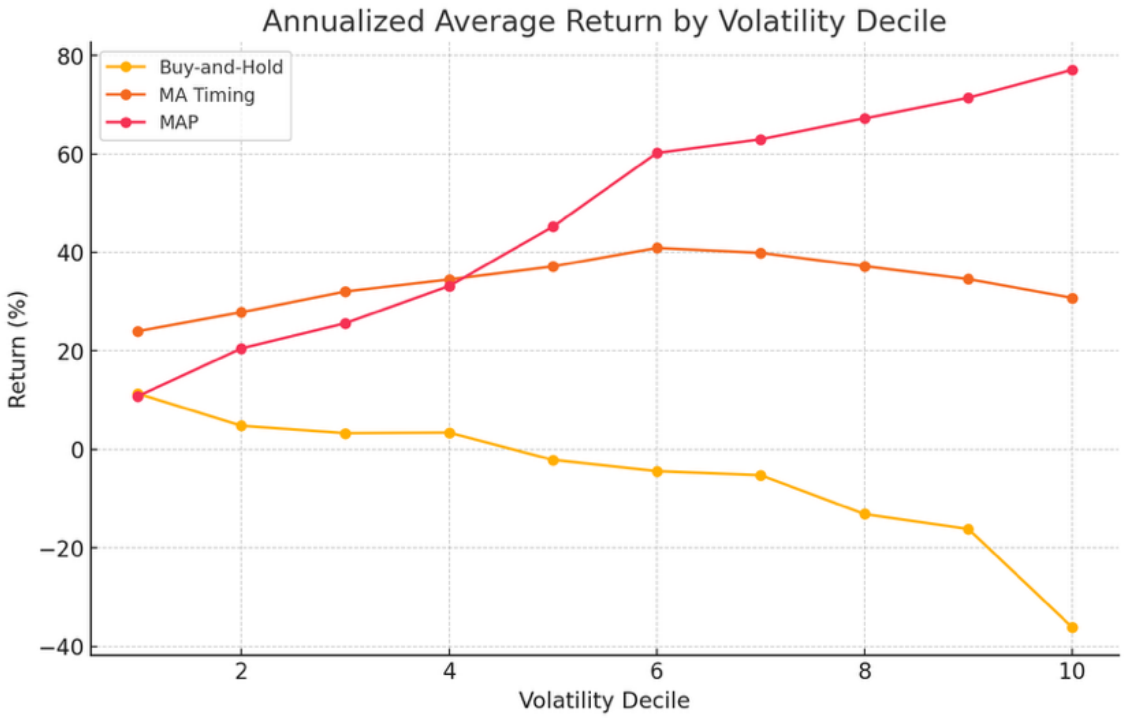

Figure 1 illustrates the annualised average returns of the three portfolio configurations - buy-and-hold, MA Timing, and MAP - plotted across deciles sorted by volatility.

The buy-and-hold strategy shows a clear downward trend, with returns worsening as volatility rises. While portfolios in the lowest deciles earn moderate positive returns, those in the highest deciles, especially Decile 10, experience significant underperformance, with average yearly losses over 35%. This inverse link between volatility and returns challenges traditional risk-return ideas and emphasizes the difficulties of holding high-volatility assets without any active risk.

The MA Timing strategy consistently outperforms the passive benchmark across all deciles. Its effectiveness appears most pronounced in the mid-volatility range, where the timing rule likely captures directional movements while avoiding excessive noise. Returns decline slightly in the top deciles, potentially reflecting the reduced signal reliability in highly erratic price environments.

The MAP curve, which isolates the contribution of the timing signal relative to the buy-and-hold benchmark, increases monotonically across deciles. The incremental returns rise with volatility and reach nearly 80% in the highest decile. This suggests that the moving average signal becomes increasingly valuable as volatility rises, not only offsetting the underperformance of the passive strategy but also generating substantial excess returns.

Overall, the figure provides evidence that the moving average strategy is most effective in volatile settings, where it can better capture persistent price movements. These findings reinforce the view that technical timing rules are particularly useful in environments characterised by elevated uncertainty and price dispersion, and that volatility-sorted portfolios can benefit from active overlays such as MAP.

It can be concluded that the MA timing strategy significantly improves portfolio performance by generating higher returns, reducing volatility, and enhancing skewness. These characteristics translate into substantially higher Sharpe ratios and a success rate that exceeds random chance, indicating effective timing ability.

## 4.2. Comparative Analysis with Han et al. (2013)

This section compares the empirical results presented in our study with those of Han et al. (2013), who investigate the performance of moving average timing strategies applied to portfolios sorted by return volatility. Their study, based on U.S. equity data from 1965 to 2010, serves as a benchmark for evaluating the robustness of the moving average approach in different markets and periods.

Han et al. (2013) report a positive and monotonic relationship between portfolio volatility and average returns in buy-and-hold strategies. Specifically, average annualised returns increase from 10.81% in the lowest-volatility decile to 44.78% in the highest, with a spread of 33.98% that is both economically and statistically significant.

By contrast, in our sample - composed of European equity portfolios over the period 2010-2024 - this pattern does not hold. While the lowest-volatility decile yields an average return of 11.31%, the highest-volatility decile presents a markedly negative return of -36.17%. The High-minus-Low return spread is -47.48%, with a Sharpe ratio of -1.1380%, indicating a strongly adverse risk-return profile for high-volatility stocks in this sample. These findings suggest that volatility may not be positively priced in all markets or periods, potentially reflecting regime shifts, macroeconomic uncertainty, or investor risk aversion during the post-crisis era particularly marked in Europe by the sovereign debt crisis (2010-2012), the COVID-19 pandemic, and the monetary tightening cycle from 2022 onward. In the subsequent chapter, it is also investigated the stability of the MA timing strategy's effectiveness across varying market conditions and temporal regimes.

Both studies converge in their findings regarding the efficacy of the moving average timing strategy. In our data, the 10-day moving average timing portfolios consistently outperform their buy-and-hold counterparts, generating significantly higher average returns (ranging from 23.97% to 40.87%) with markedly lower volatility. For instance, the standard deviation in the highest decile drops from 47.25% to 27.32%, translating into a Sharpe ratio improvement from -0.7866 to 1.4590. Han et al. (2013) report similar volatility reductions of approximately 35-45%, with Sharpe ratios often quadrupling relative to the static portfolios.

These improvements reflect the ability of moving average rules to avoid drawdowns and capture upside momentum, especially in volatile regimes. The performance gains are particularly notable in the intermediate deciles (e.g., decile 3), where our sample exhibits a Sharpe ratio of 3.7447 - among the highest observed.

Skewness statistics reinforce the benefits of moving average timing. The buy-and-hold portfolios in both studies show mostly negative skewness, indicating downside risk exposure. The moving average portfolios exhibit either reduced negative skewness or even positive skewness, suggesting improved return asymmetry. This is especially evident in the MAP: in our results, decile 1 exhibits a skewness of 2.51, and all deciles show positive skewness except deciles 5, 6, and 8. These figures imply that the timing strategy more frequently captures large positive returns while avoiding extreme losses.

The MAP - reflecting the incremental return attributable to the MA timing rule over a buy-and-hold benchmark – exhibits consistently improved characteristics. Average returns increase across most deciles, with decile 10 reaching 77.03% annually, though this non-monotonicity contrasts with the smoother pattern observed in Han et al. (2013). One potential explanation lies in sample-specific effects such as sector composition, macro shocks, or tail events disproportionately affecting high-volatility stocks.

The last column of Panel C reports the "Success" metric - defined, following Han et al. (2013), as the proportion of trading days when the MA strategy is on the correct side of the market (i.e., out of the market when returns fall below the risk-free rate, and in the market when returns are positive). While Han et al. (2013) report an average success rate of approximately 60% across deciles, the success rates observed in our sample range from 57.31% in the highest-volatility decile to 62.27% in D6, with most values clustering close to the 60% benchmark. This pattern suggests a broadly consistent level of timing accuracy, although the distribution appears more concentrated and slightly less volatile than in the original study. These results support the notion that the MA strategy retains predictive value across different market segments, albeit with some variation in effectiveness depending on volatility rank.

Our buy-and-hold portfolio results differ markedly from those of Han et al. (2013), particularly regarding the return-volatility relationship, the improvements introduced by the MA timing strategy are consistent across both studies. The moving average rule consistently improves portfolio performance by delivering higher returns, reducing risk, and enhancing skewness and Sharpe ratios. These results reinforce the value of such timing strategies as effective tools for dynamic asset allocation. Importantly, they show that moving averages can adapt well to different market environments, helping to limit downside exposure while boosting overall portfolio efficiency.

## 4.3. Profitability and Alpha

To deepen the analysis on the returns presented on the previous section, further studies on MAPs profitability were conducted, namely on the alpha generated by such strategy. To assess the alpha generated by a MAP for a particular moving average length, a CAPM regression was conducted on the zero-cost portfolio returns on the market portfolio, with $r_{MKT,t}$ corresponding to the daily excess return on the market portfolio.

$$MAP_{it,L} = \alpha_i - \beta_{i,MKT} r_{MKT,t} \text{ , } i = 1, \ldots, 10$$

In the CAPM regressions, the intercept (α) was estimated using daily portfolio excess returns over the sample period. To improve interpretability and allow for direct comparison with the literature, the estimated daily alphas were annualised by multiplying by 252, corresponding to the average number of trading days in a year. Consequently, the reported α values in Tables 2–7 represent annualised abnormal returns, expressed in percentage terms. This adjustment ensures consistency with previous empirical studies (e.g., Han et al., 2013), which also present alphas on an annual basis.

The following tables 2-7 present the main results from the regressions conducted using the MAPs returns for the different moving average lengths being studied — 5, 10, 20, 50, 100 and 200 days.

**Table 2 - CAPM Alpha from MAPs Returns - MA (5)**

| Rank | $\alpha$ | t-stat (α) | p-value (α) | $\beta$ | $Adj. R^2$ |
|---|---|---|---|---|---|
| Low | 35.18 | 12.12*** | 3.39E-33 | -3.89E-05 | 2.14E-02 |
| 2 | 38.51 | 12.90*** | 2.67E-37 | 1.04E-05 | -2.28E-02 |
| 3 | 43.45 | 12.38*** | 1.48E-34 | 4.17E-05 | 1.38E-02 |
| 4 | 43.53 | 11.77*** | 1.98E-31 | 7.09E-05 | 7.74E-02 |
| 5 | 49.14 | 12.06*** | 6.99E-33 | 4.70E-05 | 1.30E-02 |
| 6 | 50.09 | 11.78*** | 1.67E-31 | 1.07E-05 | -2.42E-02 |
| 7 | 47.83 | 9.43*** | 7.06E-21 | 3.50E-05 | -1.23E-02 |
| 8 | 53.85 | 10.28*** | 1.79E-24 | 8.16E-05 | 4.76E-02 |
| 9 | 61.51 | 9.73*** | 4.08E-22 | 8.70E-05 | 3.45E-02 |
| High | 86.54 | 7.99*** | 1.84E-15 | 7.25E-05 | -9.34E-03 |
| High - Low | 51.36 | – | – | 0.00 | – |

This table reports the CAPM regression results for zero-cost portfolios constructed from moving average timing strategies with a 5-day signal length. For each volatility decile, the estimated intercept (α) is presented as an annualised percentage return, representing the abnormal return unexplained by the market factor. The slope coefficient (β) corresponds to the portfolio's sensitivity to market excess returns, while the adjusted $R^2$ indicates the explanatory power of the model. In addition, the t-statistic and p-value associated with each alpha estimate are reported, providing evidence on the statistical significance of the abnormal returns. Significance levels are denoted by stars: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$. The sample period spans from January 2010 to December 2024.

### Table 3 - CAPM Alpha from MAPs Returns – MA (10)

| **Rank** | $\alpha$ | **t-stat (α)** | **p-value (α)** | $\beta$ | $Adj. R^2$ |
|---|---|---|---|---|---|
| Low | 26.87 | 9.72*** | 4.40E-22 | 2.93E-05 | 1.77E-03 |
| 2 | 29.36 | 10.56*** | 1.01E-25 | 3.27E-05 | 8.89E-03 |
| 3 | 30.98 | 9.83*** | 1.49E-22 | 6.11E-05 | 7.04E-02 |
| 4 | 34.44 | 10.92*** | 2.36E-27 | 7.79E-05 | 1.34E-01 |
| 5 | 37.26 | 10.33*** | 1.08E-24 | 8.73E-05 | 1.31E-01 |
| 6 | 32.96 | 9.46*** | 5.46E-21 | 3.52E-05 | 4.14E-04 |
| 7 | 39.03 | 9.27*** | 2.93E-20 | 8.47E-05 | 8.44E-02 |
| 8 | 45.04 | 10.58*** | 8.21E-26 | 1.16E-04 | 1.86E-01 |
| 9 | 42.57 | 8.05*** | 1.05E-15 | 8.56E-05 | 4.73E-02 |
| High | 51.42 | 5.91*** | 3.75E-09 | 1.60E-04 | 7.44E-02 |
| High - Low | 24.55 | – | – | 0.00 | – |

This table reports the CAPM regression results for zero-cost portfolios constructed from moving average timing strategies with a 10-day signal length. For each volatility decile, the estimated intercept (α) is presented as an annualised percentage return, representing the abnormal return unexplained by the market factor. The slope coefficient (β) corresponds to the portfolio's sensitivity to market excess returns, while the adjusted $R^2$ indicates the explanatory power of the model. In addition, the t-statistic and p-value associated with each alpha estimate are reported, providing evidence on the statistical significance of the abnormal returns. Significance levels are denoted by stars: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$. The sample period spans from January 2010 to December 2024.

## Table 4 - CAPM Alpha from MAPs Returns – MA (20)

| Rank | $\alpha$ | t-stat (α) | p-value (α) | $\beta$ | $Adj. R^2$ |
|---|---|---|---|---|---|
| Low | 17.61 | 7.03*** | 2.42E-12 | -1.04E-05 | -2.22E-02 |
| 2 | 19.53 | 7.90*** | 3.49E-15 | -1.22E-05 | -2.04E-02 |
| 3 | 26.66 | 8.70*** | 4.87E-18 | 4.80E-05 | 3.46E-02 |
| 4 | 28.64 | 9.35*** | 1.42E-20 | 7.42E-05 | 1.22E-01 |
| 5 | 26.76 | 7.93*** | 2.86E-15 | 5.42E-05 | 3.78E-02 |
| 6 | 21.63 | 6.39*** | 1.87E-10 | 2.98E-05 | -7.74E-03 |
| 7 | 26.56 | 6.66*** | 3.11E-11 | 6.27E-05 | 3.51E-02 |
| 8 | 30.71 | 7.44*** | 1.26E-13 | -1.36E-04 | 2.50E-01 |
| 9 | 31.40 | 6.30*** | 3.36E-10 | 1.17E-04 | 1.16E-01 |
| High | 26.56 | 6.66*** | 3.11E-11 | 6.27E-05 | 3.51E-02 |
| High - Low | 8.94 | – | – | 0.00 | – |

This table reports the CAPM regression results for zero-cost portfolios constructed from moving average timing strategies with a 20-day signal length. For each volatility decile, the estimated intercept (α) is presented as an annualised percentage return, representing the abnormal return unexplained by the market factor. The slope coefficient (β) corresponds to the portfolio's sensitivity to market excess returns, while the adjusted $R^2$ indicates the explanatory power of the model. In addition, the t-statistic and p-value associated with each alpha estimate are reported, providing evidence on the statistical significance of the abnormal returns. Significance levels are denoted by stars: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$. The sample period spans from January 2010 to December 2024.

## Table 5 - CAPM Alpha from MAPs Returns – MA (50)

| **Rank** | $\alpha$ | **t-stat (α)** | **p-value (α)** | $\beta$ | $Adj. R^2$ |
|---|---|---|---|---|---|
| Low | 16.20 | 6.71*** | 2.30E-11 | 2.93E-05 | 7.16E-03 |
| 2 | 16.18 | 6.55*** | 6.70E-11 | -1.24E-05 | -2.05E-02 |
| 3 | 17.86 | 6.03*** | 1.81E-09 | 4.49E-05 | 2.68E-02 |
| 4 | 16.21 | 5.38*** | 7.74E-08 | 8.34E-05 | 1.48E-01 |
| 5 | 14.13 | 4.55*** | 5.63E-06 | 7.42E-05 | 1.01E-01 |
| 6 | 17.57 | 5.22*** | 1.87E-07 | 3.09E-05 | -6.75E-03 |
| 7 | 15.66 | 4.29*** | 1.82E-05 | 6.83E-05 | 5.29E-02 |
| 8 | 13.10 | 3.65*** | 2.68E-04 | -1.28E-04 | 2.54E-01 |
| 9 | 15.10 | 3.81*** | 1.40E-04 | 1.09E-04 | 1.43E-01 |
| High | 19.95 | 2.87*** | 4.14E-03 | 3.20E-06 | -2.61E-02 |
| High - Low | 3.75 | – | – | 0.00 | – |

This table reports the CAPM regression results for zero-cost portfolios constructed from moving average timing strategies with a 50-day signal length. For each volatility decile, the estimated intercept (α) is presented as an annualised percentage return, representing the abnormal return unexplained by the market factor. The slope coefficient (β) corresponds to the portfolio's sensitivity to market excess returns, while the adjusted $R^2$ indicates the explanatory power of the model. In addition, the t-statistic and p-value associated with each alpha estimate are reported, providing evidence on the statistical significance of the abnormal returns. Significance levels are denoted by stars: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$. The sample period spans from January 2010 to December 2024.

## Table 6 - CAPM Alpha from MAPs Returns – MA (100)

| **Rank** | $\alpha$ | **t-stat (α)** | **p-value (α)** | $\beta$ | $Adj.R^2$ |
|---|---|---|---|---|---|
| Low | 11.05 | 4.49*** | 7.42E-06 | 2.48E-05 | -4.07E-03 |
| 2 | 9.98 | 4.18*** | 2.97E-05 | 7.00E-07 | -2.61E-02 |
| 3 | 16.08 | 5.55*** | 2.98E-08 | 4.91E-05 | 3.89E-02 |
| 4 | 13.31 | 4.65*** | 3.38E-06 | 7.18E-05 | 1.13E-01 |
| 5 | 10.98 | 3.64*** | 2.75E-04 | 5.99E-05 | 5.92E-02 |
| 6 | 13.25 | 3.93*** | 8.52E-05 | 3.74E-05 | 1.07E-03 |
| 7 | 12.05 | 3.60*** | 3.19E-04 | 2.26E-05 | -1.61E-02 |
| 8 | 7.11 | 2.03** | 4.24E-02 | 1.16E-05 | -2.38E-02 |
| 9 | 9.83 | 2.76*** | 5.75E-03 | 4.42E-05 | 6.94E-03 |
| High | 13.02 | 2.40** | 1.66E-02 | -2.56E-05 | -2.12E-02 |
| High - Low | 1.97 | – | – | 0.00 | – |

This table reports the CAPM regression results for zero-cost portfolios constructed from moving average timing strategies with a 100-day signal length. For each volatility decile, the estimated intercept (α) is presented as an annualised percentage return, representing the abnormal return unexplained by the market factor. The slope coefficient (β) corresponds to the portfolio's sensitivity to market excess returns, while the adjusted $R^2$ indicates the explanatory power of the model. In addition, the t-statistic and p-value associated with each alpha estimate are reported, providing evidence on the statistical significance of the abnormal returns. Significance levels are denoted by stars: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$. The sample period spans from January 2010 to December 2024.

**Table 7 - CAPM Alpha from MAPs Returns – MA (200)**

| Rank | $\alpha$ | t-stat (α) | p-value (α) | $\beta$ | $Adj.R^2$ |
|---|---|---|---|---|---|
| Low | 8.59 | 3.28*** | 1.04E-03 | 3.54E-05 | 1.25E-02 |
| 2 | 8.63 | 3.46*** | 5.54E-04 | 2.87E-06 | -2.59E-02 |
| 3 | 11.34 | 3.82*** | 1.37E-04 | 5.41E-05 | 4.61E-02 |
| 4 | 8.81 | 2.96*** | 3.10E-03 | 7.85E-05 | 1.21E-01 |
| 5 | 7.63 | 2.43** | 1.50E-02 | 8.42E-05 | 1.25E-01 |
| 6 | 11.08 | 3.31*** | 9.35E-04 | -4.37E-06 | -2.58E-02 |
| 7 | 7.34 | 2.43** | 1.53E-02 | -6.09E-07 | -2.61E-02 |
| 8 | 6.21 | 1.90* | 5.79E-02 | 5.58E-06 | -2.55E-02 |
| 9 | 3.86 | 1.26 | 2.08E-01 | 5.93E-06 | -2.54E-02 |
| High | 8.00 | 1.77* | 7.65E-02 | -4.37E-06 | -2.59E-02 |
| High - Low | -0.59 | – | – | 0.00 | – |

This table reports the CAPM regression results for zero-cost portfolios constructed from moving average timing strategies with a 200-day signal length. For each volatility decile, the estimated intercept (α) is presented as an annualised percentage return, representing the abnormal return unexplained by the market factor. The slope coefficient (β) corresponds to the portfolio's sensitivity to market excess returns, while the adjusted $R^2$ indicates the explanatory power of the model. In addition, the t-statistic and p-value associated with each alpha estimate are reported, providing evidence on the statistical significance of the abnormal returns. Significance levels are denoted by stars: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$. The sample period spans from January 2010 to December 2024.

Starting with the 10-day moving average, to allow direct comparison with Han et al. (2013), the results show that abnormal returns are substantially higher in the more volatile portfolios, with annualised alphas ranging from 26.87% to 51.42%. These findings are broadly consistent with Han et al. (2013), who also report stronger abnormal returns in riskier portfolios under short-horizon moving average rules. However, the pattern is not strictly monotonic across deciles, as some intermediate portfolios (e.g., D6 and D9) exhibit lower alphas than adjacent portfolios. Nevertheless, the highest-volatility decile still generates nearly twice the alpha of the lowest decile, providing evidence that volatility enhances the effectiveness of short-horizon moving average timing strategies.

Extending the analysis to the 5-day rule reinforces this conclusion. The high-volatility decile achieves an alpha of 61.51% compared to 35.18% for the low-volatility decile, producing a High–Low spread of 26.33 percentage points. While not perfectly monotonic across all deciles, the overall relationship between volatility and alpha remains positive and statistically robust, confirming that shorter signals capture return premia more effectively.

From the 20-day MA onwards, the relationship weakens substantially. Although high-volatility portfolios still tend to display larger alphas than low-volatility ones, the magnitude of the High–Low alpha spread narrows considerably (e.g., 26.56% vs. 17.61%, spread of 8.94), and non-monotonic patterns become more pronounced across deciles. For the 50-day rule, the High–Low spread contracts further to just 3.75 percentage points, with no clear ranking across portfolios.

This attenuation continues with the 100-day and 200-day horizons. Under the 100-day rule, the spread falls to 1.97, and while some intermediate deciles (e.g., D3 and D6) still display economically relevant alphas, many others lose statistical significance. Finally, the 200-day rule even produces a negative spread (-0.59). Several deciles fail to generate significant abnormal returns, which seems to erode the link between volatility and alpha.

Overall, the results suggest that MAP strategies are only really profitable in short-term horizons (5- and 10-day signals). In these cases, abnormal returns are statistically significant and economically meaningful, especially in high-volatility portfolios. By contrast, longer moving averages appear less responsive to short-term market dynamics, limiting their ability to capture volatility-driven return opportunities.

Compared with Han et al. (2013), these findings confirm the central role of short-term moving averages but provide a novel contribution by showing that the effect dissipates sharply as the signal horizon increases. The evidence therefore highlights the time-sensitivity of technical trading rules: while very short horizons can deliver strong abnormal performance, the profitability of MAP strategies does not extend to medium- and long-term horizons.

To provide a clearer comparison across all moving average lengths, Table 8 consolidates the estimated CAPM alphas for each volatility-sorted decile portfolio.

**Table 8 - Annualised Abnormal Returns (CAPM α) by Volatility Decile and Moving Average Length**

| Decile | MA (5) | MA (10) | MA (20) | MA (50) | MA (100) | MA (200) |
|---|---|---|---|---|---|---|
| **Low** | 35.18 | 26.87 | 17.61 | 16.20 | 11.05 | 8.59 |
| **2** | 38.51 | 29.36 | 19.53 | 16.18 | 9.98 | 8.63 |
| **3** | 43.45 | 30.98 | 26.66 | 17.86 | 16.08 | 11.34 |
| **4** | 43.53 | 34.44 | 28.64 | 16.21 | 13.31 | 8.81 |
| **5** | 49.14 | 37.26 | 26.76 | 14.13 | 10.98 | 7.63 |
| **6** | 49.14 | 32.96 | 21.63 | 17.57 | 13.25 | 11.08 |
| **7** | 50.09 | 39.03 | 26.56 | 15.66 | 12.05 | 7.34 |
| **8** | 47.83 | 45.04 | 30.71 | 13.10 | 7.11 | 6.21 |
| **9** | 53.85 | 42.57 | 31.40 | 15.10 | 9.83 | 3.86 |
| **High** | 61.51 | 51.42 | 26.56 | 19.95 | 13.02 | 8.00 |
| **High-Low** | 26.33 | 24.55 | 8.94 | 3.75 | 1.97 | -0.59 |

This table reports the annualised abnormal returns (CAPM α) for moving average timing strategies with signal lengths of 5, 10, 20, 50, 100, and 200 days. Results are shown across volatility-sorted decile portfolios, from Low to High volatility, as well as for the High–Low spread portfolio. The reported α values correspond to the intercepts from CAPM regressions, annualised and expressed in percentage terms. The sample period spans from January 2010 to December 2024.

The results confirm that abnormal returns are concentrated in the shorter moving averages (5- and 10-day signals), particularly in high-volatility portfolios. In contrast, longer horizons such as the 100- and 200-day rules show little to no evidence of abnormal returns.

These findings reinforce what was found by Han et al. (2013) when it comes to short-term strategies, especially the 10-day MAP. But as the moving average gets longer, the relationship becomes less reliable, indicating that the effectiveness of MAP strategies is highly dependent on signal length, with profitability concentrated in shorter horizons.

# 5. Robustness Tests

This section examines how robust the profitability of the Moving Average Portfolios (MAPs) proves to be under different conditions. It begins by testing whether results change when alternative lag lengths are used for the moving average signal. It then looks at the trading features of the MA timing strategy and estimates the break-even transaction cost. Lastly, it evaluates whether the profitability of the strategy is consistent across three subperiods of the sample.

## 5.1. Impact of Moving Average Lag Length on Portfolio Performance

Table 9 reports the annualised average returns of timing strategies applied to volatility-sorted portfolios, comparing six different moving average lag lengths (5, 10, 20, 50, 100 and 200 days) against the traditional buy-and-hold benchmark. This analysis helps to assess how sensitive the timing signal is to the choice of horizon and to differences in portfolio volatility.

**Table 9 - Impact of Different Moving Average Lag Lengths on Portfolio Performance**

| Decile | MA (5) | MA (10) | MA (20) | MA (50) | MA (100) | MA (200) | B&H |
|---|---|---|---|---|---|---|---|
| **Low** | 30.87% | 24.76% | 16.53% | 15.24% | 10.80% | 8.53% | 11.31% |
| **2** | 33.14% | 23.97% | 17.78% | 15.13% | 9.71% | 8.39% | 13.22% |
| **3** | 36.82% | 28.40% | 23.57% | 16.01% | 14.95% | 10.83% | 17.58% |
| **4** | 36.60% | 34.11% | 25.51% | 15.38% | 12.93% | 9.00% | 14.81% |
| **5** | 40.79% | 29.83% | 23.76% | 13.28% | 10.45% | 7.47% | 13.59% |
| **6** | 41.07% | 36.02% | 19.94% | 16.40% | 12.89% | 10.83% | 12.07% |
| **7** | 39.98% | 32.63% | 23.71% | 14.54% | 11.37% | 7.24% | 6.43% |
| **8** | 43.86% | 36.72% | 26.61% | 12.07% | 6.84% | 6.09% | 0.22% |
| **9** | 48.17% | 34.66% | 28.09% | 14.06% | 9.20% | 3.41% | -8.31% |
| **High** | 63.13% | 40.87% | 24.62% | 18.34% | 12.44% | 7.62% | -36.17% |

This table reports the annualised returns of decile portfolios sorted by volatility, under different moving average (MA) timing strategies with lag lengths of 5, 10, 20, 50, 100, and 200 days, alongside the buy-and-hold (B&H) benchmark. The sample period spans from January 2010 to December 2024.

The results show a clear variation in performance across lag lengths: shorter moving averages consistently outperform longer ones, especially in the high-volatility deciles. The 5-day rule produces the strongest returns in all portfolios, peaking at 63.13% in Decile 10. The 10-day rule, already highlighted in earlier sections, also delivers robust results across most deciles, particularly D4 to D9.

By contrast, longer moving averages (100 and 200 days) show a markedly diminished performance profile. These strategies offer less improvement over buy-and-hold and, in certain cases, only marginally outperform it. For instance, in Decile 10 - the most volatile portfolio - the MA (200) strategy returns 7.62%, while buy-and-hold yields -36.17%, showing that even slower signals provide valuable downside protection.

The pattern of returns shows that timing effectiveness is concentrated in short-term moving averages, particularly between 5 and 10 days. These short lags react quickly to market moves, allowing the strategy to capture upward trends while exiting adverse ones in time. As the lag increases, the signal becomes slower and less responsive, reducing its ability to limit losses or enhance returns.

The divergence in performance is clearest in the high-volatility deciles (D8–D10), where short-term rules not only protect against large drawdowns but also generate strong positive returns. This reverses the losses observed under buy-and-hold and suggests that volatility can be exploited productively through adaptive timing rules.

Still, in line with Han et al. (2013), even long-term signals remain economically meaningful. The 200-day rule delivers positive annualised returns across all deciles (3.41% to 10.83%), outperforming buy-and-hold in most cases. This indicates that moving averages are not purely a short-term phenomenon but retain value over different horizons.

In the lower-volatility deciles (D1–D3), the gap between short and long lags is narrower. Even 100- and 200-day rules manage to beat buy-and-hold, suggesting more stable trends in less volatile portfolios.

The evidence shows that moving average timing is highly sensitive to the chosen lag length. Short rules, particularly the 5-day, produce the largest gains, especially among the most volatile stocks. Yet the fact that all MA rules outperform buy-and-hold, regardless of lag, highlights their robustness and supports their role as a reliable portfolio enhancement tool.

## 5.2. Average Holding Days, Trading Frequency, and BETC

The results presented in the previous section indicate that shorter moving average lags consistently yield superior performance compared to longer lags, particularly within portfolios characterised by higher volatility.

As the MA timing strategy operates on a daily signal basis, it naturally raises the question of how often it triggers trades. If trading occurs too frequently, even strong returns could be offset by transaction costs, reducing the practical value of the strategy. To evaluate this risk, the analysis considers how long the strategy typically holds positions before switching – measured by the average number of consecutive days invested – as well as the total number of trades over the period. Additionally, the break-even transaction cost (BETC) is estimated, reflecting the level of trading cost at which the strategy's net return would fall to zero. This helps assess whether the reported performance is likely to survive under realistic implementation conditions.

**Table 10 - Average Holding Days per MA length**

| Decile | MA (5) | MA (10) | MA (20) | MA (50) | MA (100) | MA (200) |
|---|---|---|---|---|---|---|
| **Low** | 6.29 | 10.52 | 15.42 | 20.84 | 32.21 | 78.19 |
| **2** | 6.58 | 10.70 | 15.35 | 25.13 | 38.02 | 69.68 |
| **3** | 6.75 | 9.81 | 14.94 | 24.75 | 34.48 | 93.05 |
| **4** | 6.66 | 10.91 | 15.98 | 26.13 | 47.03 | 105.04 |
| **5** | 6.44 | 10.59 | 16.97 | 22.61 | 33.81 | 57.63 |
| **6** | 6.52 | 10.69 | 15.09 | 29.13 | 32.97 | 45.47 |
| **7** | 6.26 | 10.26 | 14.60 | 22.39 | 33.69 | 50.12 |
| **8** | 6.52 | 10.64 | 15.62 | 21.47 | 34.53 | 38.68 |
| **9** | 6.54 | 10.13 | 14.44 | 25.79 | 42.77 | 63.54 |
| **High** | 6.59 | 11.04 | 15.99 | 25.92 | 58.44 | 112.80 |

This table reports the average number of consecutive days each moving average (MA) timing strategy remained invested in the market after generating a buy signal. Results are presented for lag lengths of 5, 10, 20, 50, 100, and 200 days, across decile portfolios sorted by volatility. The sample covers the period from January 2010 to December 2024.

Table 10 shows that shorter moving average strategies hold positions for fewer consecutive days compared to longer MAs - a pattern consistent with the higher signal frequency of short lags. The average holding period ranges from just 6 days for MA (5) to over 100 days for MA (200), more accentuated in the most volatile deciles. This inverse relationship between lag length and trading frequency highlights the reactive nature of short-term MAs, which may come at the cost of increased turnover. Interestingly, longer MAs tend to hold positions slightly longer in high-volatility portfolios, suggesting that trend signals may persist more strongly in these environments. These dynamics are essential when considering implementation: higher trading frequency could erode returns if transaction costs are not sufficiently low, a concern addressed in the following analysis of break-even transaction cost levels.

Also, in the study of Han et al. (2013), the authors examined the frequency of trading implied by the moving average strategy and found that it generates relatively infrequent signals, thereby limiting the erosion of returns caused by transaction costs. They computed the break-even cost levels and concluded that the strategy remains profitable even under conservative assumptions, suggesting that transaction costs are unlikely, in any case, to fully offset the abnormal returns observed.

**Table 11 - Trading Frequency**

| Decile | MA (5) | MA (10) | MA (20) | MA (50) | MA (100) | MA (200) |
|---|---|---|---|---|---|---|
| **Low** | 69.53 | 45.40 | 32.80 | 23.20 | 16.07 | 10.67 |
| **2** | 67.13 | 45.60 | 33.07 | 19.80 | 14.53 | 10.33 |
| **3** | 65.40 | 48.07 | 33.73 | 19.67 | 17.60 | 10.27 |
| **4** | 66.20 | 44.87 | 31.53 | 18.60 | 12.47 | 8.07 |
| **5** | 68.47 | 44.60 | 29.93 | 22.27 | 14.73 | 9.47 |
| **6** | 67.93 | 44.33 | 32.60 | 20.40 | 17.33 | 12.13 |
| **7** | 70.07 | 46.20 | 34.40 | 22.67 | 16.67 | 13.60 |
| **8** | 67.73 | 44.60 | 31.53 | 22.07 | 17.20 | 14.73 |
| **9** | 66.13 | 46.80 | 33.73 | 21.33 | 14.93 | 8.20 |
| **High** | 66.53 | 43.07 | 31.87 | 18.53 | 10.87 | 7.53 |

This table presents the average number of trades - buys and sells - per year generated by each moving average (MA) timing strategy, for lag lengths of 5, 10, 20, 50, 100, and 200 days. The figures reflect how frequently the MA signal shifted between in-market and out-of-market positions. Results are reported across volatility-sorted decile portfolios for the period from January 2010 to December 2024.

Table 11 shows the average number of trades generated per year across different MA lengths. The pattern is straightforward: the shorter the lag, the more trading signals are triggered. For instance, a 5-day MA produces close to 70 trades annually, while a 200-day MA leads to fewer than 15 trades, regardless of volatility level. This is intuitive, since shorter horizons react more quickly to daily noise, whereas long lags filter out most fluctuations.

Looking across deciles, the differences are present but relatively modest. Portfolios in the upper volatility range (deciles 8–10) show slightly more signals than the lower ones, though the gap rarely exceeds three or four trades per year. For example, under the 20-day MA, high-volatility portfolios average 33–34 trades, while low-volatility ones produce around 30. This is not a dramatic divergence, but it does fit the idea that volatility increases the likelihood of price crossings.

The broader point is that frequency is driven mainly by the choice of lag length rather than volatility. This matters for implementation: a 5-day MA looks attractive on performance grounds but comes with very high turnover, which makes it vulnerable to trading frictions. Longer horizons reduce that concern, but at the cost of weaker responsiveness to market movements.

**Table 12 - Break-even Transaction Costs**

| Decile | MA (5) | MA (10) | MA (20) | MA (50) | MA (100) | MA (200) |
|---|---|---|---|---|---|---|
| **Low** | 0.51 | 0.59 | 0.54 | 0.70 | 0.69 | 0.81 |
| **2** | 0.57 | 0.64 | 0.59 | 0.82 | 0.69 | 0.84 |
| **3** | 0.66 | 0.64 | 0.79 | 0.91 | 0.91 | 1.10 |
| **4** | 0.66 | 0.77 | 0.91 | 0.87 | 1.07 | 1.09 |
| **5** | 0.72 | 0.84 | 0.89 | 0.63 | 0.75 | 0.81 |
| **6** | 0.72 | 0.74 | 0.66 | 0.86 | 0.76 | 0.91 |
| **7** | 0.71 | 0.84 | 0.77 | 0.69 | 0.72 | 0.54 |
| **8** | 0.71 | 1.01 | 0.97 | 0.59 | 0.41 | 0.42 |
| **9** | 0.81 | 0.91 | 0.93 | 0.71 | 0.66 | 0.47 |
| **High** | 0.92 | 1.19 | 0.83 | 1.08 | 1.20 | 1.06 |

This table reports the break-even transaction costs for moving average portfolios (MAPs) with different signal lengths (5, 10, 20, 50, 100, and 200 days). The break-even cost represents the maximum transaction fee, expressed as a percentage of portfolio value per trade, that would fully eliminate the abnormal returns generated by each strategy. Results are reported across volatility-sorted decile portfolios (Low to High volatility) for the period from January 2010 to December 2024.

Table 12 reports the break-even transaction costs (BETC) across lag lengths and volatility deciles. These figures represent the maximum cost per trade under which the abnormal returns of MAPs would remain positive. The results show that, in general, short lags can sustain costs in the 0.5%–0.9% range, with the high-volatility decile reaching 0.92% under the 5-day MA. This makes sense: riskier portfolios tend to generate larger swings and therefore create more room to absorb frictions.

The picture becomes less tidy when moving to longer horizons. In some cases, the thresholds remain high - the 100-day MA for the top decile can tolerate more than 1% per trade - but in others, the margins collapse. Under the 200-day MA, for example, mid- to high-volatility portfolios can only bear 0.4%-0.5%, which would likely be insufficient once realistic costs are factored in. This mixed pattern highlights the trade-off: longer moving averages reduce trading frequency but also leave less abnormal return to cover costs.

These results indicate that short horizons, especially when applied to volatile portfolios, can survive under plausible transaction costs, whereas long horizons look fragile once frictions are introduced. The BETC measure is therefore useful to distinguish strategies with genuine economic value from those that only appear profitable from those that only appear profitable in historical simulations.

Taken together, Tables 11 and 12 underline the trade-off faced by moving average strategies. Short lags generate many signals – almost daily in the case of the 5-day MA – which raises concerns about trading intensity but also comes with relatively high break-even thresholds, especially in the more volatile portfolios. Longer lags, however, look safer in terms of turnover, yet the margins to cover costs quickly shrink, and in some deciles, they fall to levels that are hardly realistic in actual markets. The practical implication is that performance cannot be assessed by looking at returns alone: trading frequency and the ability to withstand frictions need to be considered together to judge whether these strategies truly offer economic value.

### 5.3. Subperiod Performance Analysis

Table 13 shows that the performance of the MAP strategy improves as portfolio volatility increases. Average returns move from 13.45% in the lowest-volatility decile (D1) to 77.03% in the highest (D10), suggesting that the strategy is more effective in capturing trends in more volatile stocks. However, the performance is not stable over time. Several early years (e.g., 2010, 2013, and 2015) show weaker returns across many deciles, while the more recent period from 2020 to 2023 records consistently strong returns, especially in the top deciles.

## Table 13 - Annual returns obtained by each volatility-sorted decile portfolio under the 10-day Moving Average Strategy

| Decile | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 | Avg. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Low** | 6.27% | 9.84% | 9.10% | -13.14% | 5.22% | -13.60% | 14.93% | 11.15% | 1.28% | 8.61% | 28.81% | 8.59% | 98.69% | 14.70% | 11.31% | **13.45%** |
| **2** | 27.12% | 15.60% | -7.48% | -16.88% | 38.06% | 6.28% | 4.43% | -5.30% | 6.30% | 11.87% | 15.07% | -1.84% | 39.48% | 23.36% | 5.16% | **10.75%** |
| **3** | -0.09% | 8.66% | 22.28% | 4.93% | 4.54% | 7.47% | 22.45% | -21.28% | 8.17% | 5.76% | 10.06% | 12.91% | 35.59% | 54.33% | -13.39% | **10.83%** |
| **4** | 38.48% | 10.43% | 66.06% | -12.79% | -10.42% | 23.95% | 8.40% | -9.30% | 12.03% | 33.28% | 22.94% | 15.88% | 35.71% | 39.15% | 15.76% | **19.30%** |
| **5** | -27.15% | 43.43% | 29.19% | -12.40% | -7.15% | 28.51% | 13.51% | 1.91% | 10.39% | 30.79% | 14.47% | 10.14% | 52.53% | 29.99% | 25.35% | **16.23%** |
| **6** | -28.42% | 22.27% | 47.12% | 8.29% | 40.93% | 8.45% | 14.81% | 20.91% | 26.51% | 52.56% | 22.84% | 1.48% | 48.67% | 58.61% | 14.19% | **23.95%** |
| **7** | 2.96% | 4.21% | 52.53% | 14.76% | 4.92% | 36.10% | 36.13% | 22.93% | 9.44% | 44.23% | 20.58% | -9.95% | 90.15% | 41.70% | 22.41% | **26.21%** |
| **8** | -105.54% | 136.57% | 47.93% | 37.05% | 29.37% | 28.73% | 19.65% | 52.05% | 41.58% | 72.15% | 41.76% | 47.02% | 59.59% | 45.22% | -5.60% | **36.50%** |
| **9** | 106.59% | 43.82% | 77.44% | 41.72% | 36.04% | 16.69% | 24.42% | 25.68% | 38.56% | 58.35% | 21.56% | 15.34% | 50.13% | 59.96% | 28.20% | **42.97%** |
| **High** | -44.97% | 102.93% | 105.42% | 84.77% | 80.59% | 88.48% | 165.91% | 75.90% | 68.58% | 75.34% | 71.60% | 80.61% | 78.60% | 95.52% | 26.23% | **77.03%** |
| **Avg.** | **-2.48%** | **39.77%** | **44.96%** | **13.63%** | **22.21%** | **23.11%** | **32.47%** | **17.47%** | **22.28%** | **39.29%** | **26.97%** | **18.02%** | **58.91%** | **46.25%** | **12.96%** | **27.72%** |

This table presents the annual returns for MAP strategy under 10-day moving average, and the MAPs - defined as the difference between the MA timing portfolios and the respective buy-and-hold returns. The sample period spans from January 2010 to December 2024.

To complement this analysis, Figure 2 provides a heatmap of annual returns across deciles and years. The visual representation reinforces the findings from table 13 and reveals additional insights. First, the concentration of dark green cells in high-volatility portfolios, particularly D9 and D10, confirms their consistently strong performance, with several years delivering returns above 50%. In 2016, D10 achieved +165.91%, reflecting the ability of the MAP strategy to capture large directional movements.

## Figure 2 - Heatmap of Annual Returns

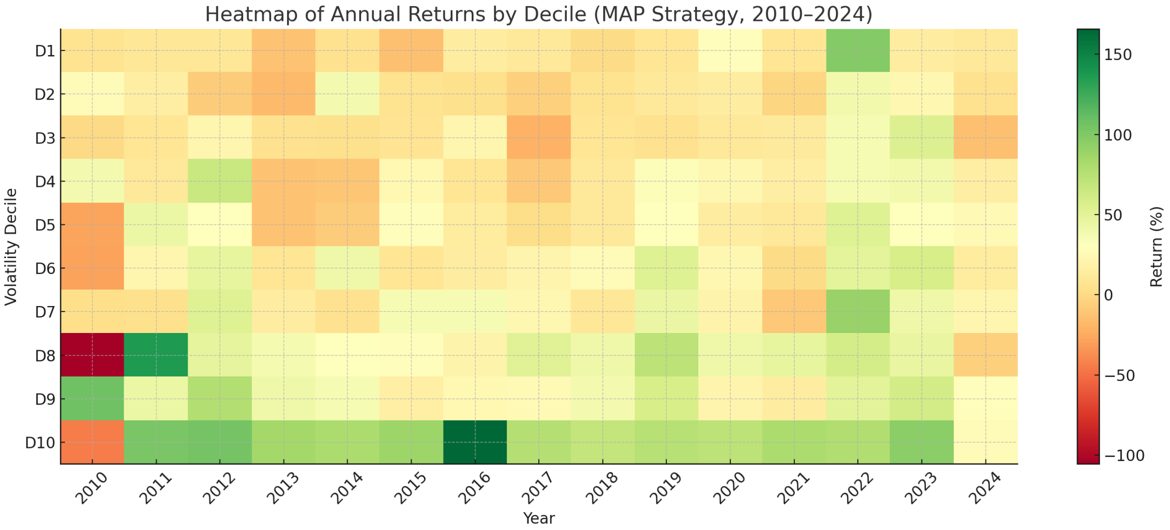

Figure 2. Heatmap of annual returns by volatility decile for the MAP strategy, 2010–2024

The heatmap reveals several key insights. First, it confirms the strong performance observed in high-volatility portfolios, particularly D9 and D10, which exhibit clusters of dark green cells in years such as 2016, 2021, 2022, and 2023. These portfolios frequently delivered returns well above 50%, and in some years - most notably D10 in 2016 (+165.91%) - exceeded 100%. Such extreme values suggest that the MAP strategy successfully captured persistent trends and large price movements in volatile stocks, a behaviour consistent with the findings of Han et al. (2013). Second, the heatmap highlights the erratic and uneven performance of the lower-volatility deciles (D1 to D3). These portfolios show a mix of modest green and pale or red cells, indicating lower and more variable returns. For example, D1 registered negative or near-zero returns in 2013 (-

13.14%) and 2015 (-13.60%), which likely resulted from false trading signals generated in sideways or low-volatility markets - a known weakness of moving average strategies. This pattern reinforces the idea that market regimes heavily influence the effectiveness of timing rules: in calm or directionless markets, signal quality deteriorates, and strategy performance weakens.

Third, the heatmap reveals a temporal dimension to the strategy's performance. Years such as 2010, 2013, and 2018 show overall weaker performance across many deciles, whereas 2020 to 2023 stand out as particularly profitable periods. These more recent years coincide with the post-COVID recovery, elevated uncertainty, and strong sectoral rotations, conditions that often favour technical timing strategies. The widespread strong performance across most deciles during this subperiod indicates a market regime highly conducive to trend exploitation.

Notably, some extreme outliers appear in mid-volatility deciles as well. For instance, D8 in 2011 delivered +136.57%, and D3 in 2023 reached +54.33%, highlighting that, under certain conditions, even lower-decile portfolios can experience strong MAP-driven gains. These outcomes may result from localized market inefficiencies or specific sectoral exposures within those portfolios during those years.

The heatmap supports the rationale for conducting a subperiod analysis, as return patterns are not stationary. The observed regime shifts - from weak early years (2010-2014) to high-performing recent years (2020-2023) - imply that market structure and volatility dynamics are critical for understanding the success or failure of technical strategies like MAP.

The presented heatmap provides evidence that the 10-day MAP strategy performs best under two key conditions: high asset volatility and high market-wide uncertainty. the evidence confirms that moving average strategies work best in trending and volatile markets, and that performance should always be assessed with changing market regimes in mind.

**Table 14 - Average return for different subperiods**

| Decile | 2010-2014 | 2015-2019 | 2020-2024 |
|---|---|---|---|
| Low | 3.37% | 4.33% | 32.47% |
| 2 | 11.19% | 4.59% | 16.28% |
| 3 | 7.98% | 4.39% | 19.93% |
| 4 | 18.26% | 13.53% | 25.95% |
| 5 | 5.09% | 16.89% | 26.55% |
| 6 | 17.94% | 24.50% | 29.21% |
| 7 | 15.77% | 29.61% | 33.03% |
| 8 | 28.98% | 42.67% | 37.65% |
| 9 | 61.00% | 32.59% | 35.10% |
| High | 65.61% | 94.66% | 70.55% |

This table reports the average returns of decile portfolios sorted by volatility under the 10-day moving average (MA) timing strategy, across three distinct subperiods: 2010–2014 (post-financial crisis recovery), 2015–2019 (pre-pandemic stability), and 2020–2024 (pandemic and post-pandemic volatility). The results highlight the variation in performance across both time and volatility levels, providing insights into the regime dependence of MA-based timing strategies. The sample spans January 2010 to December 2024.

To assess whether the performance of the MAP strategy varies across different market environments, this section evaluates returns across three distinct subperiods: 2010-2014 (post-financial crisis recovery), 2015-2019 (pre-pandemic stability), and 2020-2024 (pandemic and post-pandemic volatility). Table 14 presents the average annual returns for each volatility decile within these periods.

The results demonstrate a clear regime dependence in the effectiveness of the MAP strategy. During 2010-2014, returns were relatively modest in the lower deciles: D1, D2 and D3 recorded average annual returns of 3.37%, 11.19%, and 7.98%, respectively. In contrast, higher-volatility portfolios (D9 and D10) delivered significantly stronger performances of 61% and 65.61%, suggesting that even in more stable periods, the strategy can effectively capture trends in volatile assets.

In the 2015-2019 subperiod, performance in the lower deciles remained muted (e.g., D1 at 4.33%, D3 at 4.39%), while mid- to high-volatility portfolios saw substantial gains. D5 almost tripled its return compared to the previous subperiod (from 5.09% to 16.89%), and D10 reached an impressive 94.66% - the highest five-year average across the full sample. These results align with a period of steady growth and ample liquidity, where technical momentum strategies are often favoured.

In the final subperiod (2020-2024), returns increased across the board. D1 surged to 32.47%, while mid-deciles such as D4, D5, and D6 maintained solid performances between 25% and 30%. Although D10 declined slightly to 70.55%, it remained the best-performing portfolio overall. These findings are consistent with expectations for the COVID and post-COVID period, which was marked by increased uncertainty and directional trends that favour rule-based timing strategies.

The strong performance across all deciles during this period reinforces the hypothesis that MAP strategies are most effective in environments with persistent volatility and trend opportunities. Even traditionally lower-risk portfolios (e.g., D1-D3) saw dramatic increases in performance, indicating a broad-based improvement in timing signal quality during periods of systemic market stress and recovery. The subperiod analysis confirms that the MAP strategy exhibits time-varying effectiveness. Its performance is enhanced in volatile, uncertain, and momentum-driven regimes, while more subdued in calm or range-bound markets. This evidence supports the argument that technical trading rules such as moving averages should be evaluated dynamically, accounting for the prevailing market regime, rather than relying solely on full-sample performance metrics.

### 5.4. Rate of Success analysis

Table 15 reports the success rate of the MA timing strategies across different lag lengths, defined as the percentage of days in which the MA signal correctly anticipated market direction, being out of the market on negative-return days and invested on positive-return days. The sample covers the period from January 2010 to December 2024 and includes six lag configurations (5, 10, 20, 50, 100, and 200 days) applied across decile portfolios sorted by volatility.

### Table 15 - Rate of Success for Different Moving Average Lag Lengths

| Decile | MA (5) | MA (10) | MA (20) | MA (50) | MA (100) | MA (200) |
|---|---|---|---|---|---|---|
| **Low** | 64.92% | 61.43% | 57.21% | 56.63% | 54.91% | 57.07% |
| **2** | 67.31% | 62.02% | 57.82% | 57.27% | 55.32% | 56.78% |
| **3** | 65.00% | 59.72% | 57.16% | 55.43% | 55.07% | 54.99% |
| **4** | 65.65% | 62.07% | 59.07% | 55.94% | 54.46% | 53.73% |
| **5** | 65.03% | 60.97% | 57.58% | 55.50% | 54.72% | 53.03% |
| **6** | 65.14% | 62.27% | 58.11% | 55.79% | 55.30% | 54.76% |
| **7** | 64.42% | 60.43% | 58.44% | 55.94% | 55.05% | 53.94% |
| **8** | 62.63% | 59.84% | 56.19% | 54.58% | 52.83% | 53.15% |
| **9** | 63.68% | 59.12% | 57.66% | 54.40% | 52.41% | 46.52% |
| **High** | 62.02% | 57.31% | 54.20% | 52.30% | 54.97% | 39.00% |

This table presents the success rate of each strategy, defined as the proportion of days in which the moving average (MA) signal correctly anticipated market direction - that is, being out of the market on days with negative returns and invested on days with positive returns, when compared to the risk-free asset. Results are reported for MA timing strategies with lag lengths of 5, 10, 20, 50, 100, and 200 days. The sample period spans from January 2010 to December 2024.

Table 15 reports the success rate of the MA timing strategies across different lag lengths, defined as the percentage of days in which the MA signal correctly anticipated market direction, being out of the market on negative-return days and invested on positive-return days. The sample covers the period from January 2010 to December 2024 and includes six lag configurations (5, 10, 20, 50, 100, and 200 days) applied across decile portfolios sorted by volatility.

Results show that shorter moving averages, particularly the 5-day and 10-day variants, consistently exhibit higher success rates across almost all deciles. For example, Decile 2 achieves a success rate of 67.31% with MA (5), compared to just 56.78% with MA (200). The pattern holds across the spectrum: even in lower-volatility portfolios such as D1, the difference between MA (5) and MA (200) is notable (64.92% vs. 57.07%).

The decline in performance with increasing length of the MA applied is particularly evident in higher-volatility portfolios. In Decile 10, success rates drop sharply from 62.02% under MA (5) to only 39.00% with MA (200), suggesting that slower signals are less able to adapt to fastchanging market conditions. These results reinforce earlier findings that short-term MAs are more effective at capturing directional shifts, especially in volatile environments.

This pattern is broadly consistent with Han et al. (2013), who observed a similar sensitivity to lag length in U.S. data. The findings confirm that the effectiveness of technical timing strategies depends not only on the underlying asset characteristics (e.g., volatility) but also on the responsiveness of the signal itself.

The success rate analysis adds a complementary dimension to the return-based evaluation presented earlier. While short-term MAs were already shown to yield higher returns and Sharpe ratios, the success rate metric provides further evidence that these strategies are capturing genuine directional patterns, rather than benefiting from random variation or overfitting. The robustness of the results across deciles and lag specifications reinforces the case for using adaptive MA signals in the design of tactical asset allocation strategies.

# 6. Conclusion

This dissertation investigated the effectiveness of moving average timing strategies applied to European equity portfolios, sorted by volatility deciles, building upon the seminal framework of Han et al. (2013). By extending their methodology from the United States to the European context, this study provides new evidence on whether technical strategies retain predictive power in markets with different institutional, regulatory, and behavioural dynamics.

The findings of this study demonstrate that MA-based strategies substantially improve the risk–return profile of equity portfolios when compared to a passive buy-and-hold benchmark. In particular, the evidence shows that abnormal returns are concentrated in the higher-volatility deciles, where short-horizon moving average strategies (e.g., 5-day and 10-day signals) deliver economically meaningful and statistically significant alphas. This effect is especially pronounced in the upper volatility portfolios (e.g., D8, D9, and High), consistent with Han et al. (2013), who also find that short-horizon rules tend to generate stronger abnormal returns in riskier portfolios. These results broadly mirror those documented by Han et al. (2013) in U.S. markets, suggesting that the "new anomaly" of volatility-conditioned trend-following is not limited to a single geography but instead reflects a more generalisable mechanism across developed equity markets. At the same time, differences emerge: the magnitude of alphas in the European setting is somewhat lower, consistent with more integrated capital markets and the possibility of tighter arbitrage constraints relative to the United States.

Theoretically, these findings contribute to the debate on the limits of the Efficient Market Hypothesis. The persistence of predictable patterns based on simple technical rules challenges the weak-form of efficiency by showing that past price information can still be systematically exploited. Moreover, the results highlight the interaction between volatility and behavioural biases such as underreaction, disagreement, and noise trading, which are more pronounced in high-volatility environments. In this sense, volatility does not merely serve as a proxy for risk, as assumed in traditional asset pricing models, but also captures dimensions of mispricing and informational inefficiencies.

From a practical perspective, the results underline the continued relevance of technical analysis despite long-standing academic scepticism. For portfolio managers and institutional investors, the evidence suggests that volatility-conditioned MA strategies can serve as cost-effective and easily implementable market-timing rules, particularly in turbulent market conditions where standard models may underperform. For regulators, the persistence of such anomalies raises questions about the completeness of price discovery in European equities and suggests that behavioural distortions may play a structural role even in highly liquid markets.

Robustness checks further strengthen the credibility of the results. Average holding period calculations and break-even transaction cost estimates indicate that implementation frictions are unlikely to fully erode profitability, at least for shorter-term MA strategies in volatile deciles. This enhances the practical applicability of the findings, suggesting that relatively simple trading rules can provide consistent performance improvements within real-world investment structures.

This dissertation therefore makes three key contributions: (i) it extends the evidence on moving average timing strategies beyond the U.S. market, confirming their relevance in Europe; (ii) it deepens the theoretical debate by linking volatility to behavioural explanations of return predictability; and (iii) it highlights the practical value of volatility-conditioning for systematic investment strategies.

Nevertheless, the study has some limitations. It focuses on European equities between 2010 and 2024, a period shaped by extraordinary events such as the sovereign debt crisis, the COVID-19 pandemic, and monetary policy shifts. Transaction costs were estimated through break-even thresholds rather than incorporating real-world frictions such as slippage or liquidity constraints. These factors may influence the magnitude of abnormal returns and their persistence over time.

Future research could extend this framework by: (i) testing alternative timing mechanisms such as exponential moving averages or machine learning-based trend filters; (ii) examining how the effectiveness of MA strategies interacts with macroeconomic regimes, including crises, monetary policy cycles, or volatility clustering; and (iii) incorporating firm-level characteristics, liquidity constraints, or investor heterogeneity to better understand why these anomalies persist.

An important implication of this research is that relatively simple strategies can nonetheless provide valuable insights into market dynamics. Although technical analysis has often been dismissed within academic circles, the persistence of moving average effects - particularly in high-volatility environments - highlights that financial markets continue to be shaped by behavioural and institutional forces not fully captured by traditional asset pricing models. This recognition reinforces that financial markets, even in highly developed markets, remain fertile ground for systematic strategies and continued academic research.

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