LUISS

Department
of Business and Management

Course of Asset Pricing

The predictive abilities of technical analysis-based recommendations for various asset classes

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Academic Year 2020/2021

Acknowledgements

The author would like to thank Prof. Straetmans from Maastricht University for the productive meetings and all feedback, BTAC Visual Analysis for providing a crucial aspect of the dataset, as well as friends and family who provided support throughout the process.

Abstract

Among academics and practitioners, there is much controversy surrounding the merits of technical analysis (TA). Current literature mainly focused on the profitability of technical trading rules, whereas evidence on the accuracy of TA-based recommendations is sparse. We performed event study analysis on technical recommendations for European stocks, global indices, commodities and forex that have been published by professional analysts between 2016 and 2021. Recommendations on stocks, indices and commodities followed short-term upward trends. Abnormal returns of recommended stocks were positive and significant in economic and statistical terms during the period following published recommendations, while recommended indices and commodities yielded significantly negative risk-adjusted returns in the post-recommendation period. Abnormal forex returns increased up to the recommendation day, and this trend persisted during the post-recommendation period. However, these values were less pronounced in terms of economic and statistical significance. In addition, we compared the determinants and profitability of TA-based recommended stocks relative to FA-based recommended stocks. The fundamentally recommended equities outperformed the technically recommended equities in the period prior to the recommendation but significantly underperformed during the weeks following recommendations. The Covid-19 crisis and its associated stock market crash in March 2020 did not impact the results. Overall, we conclude that technical analysts possess distinctive predictive skills with regard to stocks.

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1. Introduction

Classic finance theory states that predicting the future price movements of stocks is a complex task. Yet, many stock market analysts issue recommendations about the future trends of various securities. As a result, academic research has covered the implications of these analyst recommendations thoroughly. However, this literature consists almost solely of recommendations that are based on fundamental analysis, while its technical counterpart remains relatively uncharted in this regard (Gerritsen, 2016). Some of these analysts and traders claim they can beat the market by means of technical analysis (TA), which has become a popular strategy (Zaloom, 2003). If this is the case, it would imply that the Efficient Market Hypothesis (Fama, 1970), which states that all available information is already incorporated in stock prices, does not hold. Since analyst recommendations are publicly available, investors should not be able to profit from them.

TA is one of the two main approaches used by investors and traders to forecast price developments of securities. Investors, traders and analysts who employ TA are also called “chartists” or “technicians”. TA is based on historical stock prices and trading volume and finds its roots in the Dow Theory (Murphy, 1999). The alternative commonly used approach to predict price trends is fundamental analysis, which focuses on estimating intrinsic values of securities based on economic factors. As a result of the Covid-19 crisis and the opportunities that came with it due to increasingly volatile financial markets and the stimulus packages from governments, many retail investors have opened trading accounts (Ortmann et al., (2020). Additionally, a broad range of TA indicators and tools are easily accessible nowadays. Menkhoff (2010) found that 87% of fund managers view TA at least as a relatively important source of information and that it dominates fundamental analysis when making investment decisions with a forecast horizon up to a few weeks. According to Taylor and Allen (1992), 90% of foreign exchange market dealers rely on both FA and TA. Moreover, according to Menkhoff (2010), TA is the most frequently used trading strategy in the foreign exchange and commodity futures markets. With regard to non-professional investors, Hoffmann and Shefrin (2014) stated that TA is more popular than fundamental analysis among individual investors. Therefore, understanding the consequences of using TA is highly important, since it impacts a large portion of both professional and retail investors.

Common tools of TA concern technical indicators, stop loss, stop gain and RSI filters (Teixeira & Inacio de Oliveira, 2010). Although traders commonly use these TA tools in practice, academic research that covers the effectiveness of TA is relatively lacking (Alanazi & Alanazi, 2020). Most papers aimed to address this research gap by testing whether investment strategies based on technical trading rules yield abnormal returns in particular markets and time periods. Park and Irwin (2007) provided an overview of such academic articles up to 2004 and concluded that a clear consensus among researchers is missing, but most evidence seems to point towards a positive relationship between technical trading rules and profitability. While some more recent papers that focus on trading rules based on sophisticated algorithms also showed that TA could lead to abnormal returns (e.g. Teixeira & Inacio de Oliveira, 2010; Sezer et al., 2017), others fail to identify the value of TA (e.g. Shynkevich, 2011). However, according to Park and Irwin (2007), a substantial portion of the studies they reviewed are subject to problems relating to ex-post selection of technical trading rules, data snooping and estimating risk and transaction costs. As outlined by Bajgrowicz and Scaillet (2012), most of the studies that showed a positive relationship between trading rules and abnormal returns should be disregarded as the relationship becomes negative after adjusting for data snooping bias. In addition, research on strict trading rules only emphasised the efficacy of TA-based trading rules, which represents only a portion of TA techniques (Roscoe & Howorth, 2009). As a result, this stream of research only provides implications about the potential of TA ex-post and not about the observed performance of investors who employ TA strategies.

Therefore, as the theoretical performance of TA may not represent investors in the real world, empirical evidence regarding the link between TA and investor decisions may lead to more realistic and valuable insights. However, surprisingly little research has been conducted on the actual effects of employing TA on (individual) investor returns. As stated by Hoffmann and Shefrin (2014), the intersection between the literature on investor returns and the literature on TA is sparse. Among the few papers that aimed to discover this intersection, Lewellen et al. (1980) and Hoffmann and Shefrin (2014) researched the linkage between TA and individual investors and both found that using TA negatively influences the portfolios of individual investors.

In response to the academic criticism they face, many TA users claim that TA involves much more than simply following trading rules and that it relates more to art than science (Gerritsen, 2016). In order to take into account the broader perspective of TA instead of only TA-based trading signals, focusing on the recommendations that are published by technical analysts may provide more insights. Research covering the profitability of buy or sell recommendations issued by (professional) technical analysts is limited. Cowles (1933) found that recommendations from technical analysts that were published in the Wall Street Journal underperformed the buy-and-hold strategy. Brown, Goetzmann and Kumar (1998) used the same dataset as Cowles (1933), but they employed different statistical methods and concluded that the Wall Street Journal recommendations yielded risk-adjusted abnormal returns. Dawson (1985) examined whether TA-based investment recommendations by a Singapore investment advisory firm would help investors to earn excess returns, but his results suggest that the recommended shares traded on the Singapore Stock Exchange did not outperform the market. Given that the general performance of TA appears the be diminishing (Neely & Weller, 2003; Pukthuanthong et al., 2007; Shynkevich, 2011), the fact that these papers are not recent is one of their main drawbacks. Another limitation concerns the fact that these papers did not consider the success of TA in the short term, although Menkhoff (2010) stated that investors typically use TA for a short investment horizon.

Gerritsen (2016) also investigated the value of TA from this angle. In fact, he examined whether these TA-based recommendations lead to future abnormal returns and concluded that this is not the case. His findings are only based on Dutch stocks and the main Dutch index, namely the AEX. He also found that the recommendations used by the technical analysts follow standard technical trading rules, which implies that TA does not seem to add value for investors. As a consequence, the results of Gerritsen (2016) contradict the more recent line of research that emphasises the positive (ex-post) results of employing TA-based trading rules based on neural networks. Surprisingly, Gerritsen (2016) seems to be the only recent paper that investigated the direct linkage between TA-based investment recommendations and stock returns.

Overall, the results of current literature suggest that there is no consensus among academics regarding the profitability of TA, and focuses mainly on technical trading rules. The fact that research covering the association between technical recommendations and stock returns is minimal, combined with the notion that many investors consider TA when making investment decisions, demands further investigation with regard to this relationship. Therefore, the problem statement we aim to examine is whether analyst recommendations that are solely based on technical analysis are associated with abnormal future returns. Although TA is most popular among investors who focus on commodities and forex markets (Menkhoff, 2010), no evidence exists on the relationship between technically recommended commodities and forex, and their returns. As a result, we aim to investigate whether technical analysis works better for stocks, forex, indices or commodities. Given that many chartists are trend-seekers, who pursue to identify stocks based on their momentum (Roscoe & Howorth, 2009), we explore whether buy recommendations follow positive abnormal returns. Finally. no paper has directly compared the performance of TA-recommended stocks to their fundamental counterparts. This leads to the question whether technical analysts have superior or inferior predictive skills regarding stock prices compared to fundamental analysts. In order to answer the problem statement and accompanying research questions, we employ event study analysis based on recommendations that have been issued between 2016 and 2021.

Relative to existing research, this study contributes to academic literature as it involves more recent data, differentiates between various types of investment vehicles, considers equities from multiple countries, and because it provides a comparison between the abnormal returns of TA and FA recommended stocks. Since existing literature mainly emphasised the profitability of technical trading rules (in isolation), this paper contributes to the level of understanding regarding the determinants and profitability as it circumvents data snooping issues and encompasses the full definition of TA. Namely, technical analysts may base their recommendations also on a visual analysis of the data as well as “gut feeling”, which cannot be measured with technical trading rules. Additionally, the results of this thesis would have implications for the ongoing debate regarding the validation of the Efficient Market Hypothesis, as this paper tests whether the market is weak-form efficient.

As the effect of TA on investor performance impacts a large number of investors, this topic is relevant to both individual and professional investors, regardless of whether they currently employ TA or not, as well as to brokers, academics and market supervisors. In fact, if TA has a negative impact on stock returns, many investors and traders are at risk in terms of financial wellbeing. Depending on the soundness of employing TA, these practitioners should be aware of the consequences of employing TA when making investment decisions. As this study also covers the profitability of FA, the exact implications apply to investors who follow FA-based recommendations or use fundamental investment techniques themselves.

The paper proceeds as follows. The next section discusses existing literature covering TA in the context of various asset classes and its relation to FA and encompasses the hypothesis development. The third section disserts the data retrieval and methodology. The fourth section shows tests of the hypotheses and their results. The fifth section discusses and interprets the findings, whereas the sixth section presents robustness tests. The final section concludes.

2. Literature Review and Hypotheses

Many traders and investors use technical analysis as an investment strategy (Menkhoff, 2010). Although many traders employ TA as a means to analyse all types of financial assets, it is the most frequently used investment strategy in the foreign exchange and commodity markets. Its popularity is partly explained by the fact that TA tools are widely available and easily accessible. Another reason is related to its simplicity since even traders without a finance background can rely on standardised trading rules that indicate when one should buy or sell an asset. TA is mainly based on data that stem from historic prices or trading volume (Park & Irwin, 2007). Pring (2002, p. 2), an influential technical analyst, provides a more concrete definition: “The technical approach to investment is essentially a reflection of the idea that prices move in trends that are determined by the changing attitudes of investors toward a variety of economic, monetary, political, and psychological forces. The art of technical analysis, for it is an art, is to identify a trend reversal at a relatively early stage and ride on that trend until the weight of the evidence shows or proves that the trend has reversed.” Pertaining to this definition, some academics and practitioners view TA as a self-fulfilling prophecy (Menkhoff, 1997). The most common TA tools and indicators are trading range breakout (TRB), moving averages, Bollinger bands, relative strength index (RSI), moving average convergence divergence (MACD), and on-balance volume (Gerritsen, 2016).

In case certain methods that are based on TA allow traders to consistently outperform the market, a buy-and-hold strategy or generate abnormal (risk-adjusted) returns, the Efficient Market Hypothesis (Fama, 1970) does not hold. More precisely, such outperformance would contradict the weak form of the Efficient Market Hypothesis. Weak-form market efficiency articulates that all information concerning past trading data is already incorporated in current

prices. Related to the Efficient Market Hypothesis, the random walk hypothesis (Fama, 1965) states that future movements of stock or market prices cannot be predicted based on their past movements or trends as all new information is directly absorbed by the market and thus reflected in the prices. Therefore, only unanticipated news or events can lead to price changes, independent of past prices or trading volume. In this regard, extrapolating past changes in prices to future price changes using TA should have no value for traders or investors. Nevertheless, since the 1960s, extensive research has been conducted on the profitability of TA (Park & Irwin, 2007).

Existing research aims to identify the value of investments in four ways. The largest portion of this research covered the merits of technical trading rules. Another approach focused on the intersection between TA, stock returns and individual investor behaviour. The remaining two categories assessed the value of TA on the basis of the combined value of fundamental and technical analysis and based on technical analyst recommendations.

2.1. Technical trading rules

Most of the academic literature that covers TA focuses on the profitability of TA-based trading rules. Park and Irwin (2007) have comprehensively reviewed the papers that cover TA and categorised this literature into two groups, namely early studies (1960-1987) and modern studies (1988-2004). In general, the early studies failed to find evidence of the profitability of technical trading rules in the stock market, whereas many studies covering foreign exchange and futures markets were able to find significant net profits. Notwithstanding, these early studies face substantial limitations. For instance, they did not consider trading rule optimisation, data snooping issues, and they only tested one or two trading rules. With regard to the modern studies, 20 studies found negative results concerning TA-based signals, 56 studies obtained positive findings and 19 studies arrived at mixed results. Particularly, modern studies found that technical trading rules yielded significant economic returns in the stock, forex and futures markets only until the early 1990s.

Although the modern studies improved upon the limitations of the early studies by taking into account the risk of trading rules, testing more trading rules, employing parameter optimisation and using more sophisticated bootstrap methods, most of them still contained data snooping biases. Data snooping biases arise due to the fact that researchers will eventually find that technical trading rules yield returns that are higher than the market return or the buy-and-hold strategy if they try enough rules with enough variables (Jensen, 1967). Essentially, positive results found by studies that do not accurately account for data snooping may not necessarily be replicated when the TA-based rules are actually employed in practice.

One approach to deal with data snooping bias concerns the application of a new dataset on a previous study and then replicate the methodology (e.g. Lo & MacKinlay, 1990; Schwert, 2003). Another way to address data snooping is to adopt White's (2000) bootstrap reality check methodology. Shynkevich (2011) used these techniques to adjust for data snooping and examined whether technical trading rules yield superior predictive accuracy when applied to small-cap sector and technology industry portfolios between 1995 and 2010. He focused on small-cap and technology stocks as equity classes with relatively high market betas tend to be driven by non-fundamental factors, in which case TA should be more useful (Menkhoff, 2010). Therefore, technology and small-cap stocks represent a natural sample of stocks where TA should be more effective. Similar to the results of Park and Irwin (2007), the findings of Shynkevich (2011) pose that TA-based signals are able to outperform the buy-and-hold strategy for both small-cap and technology portfolios in the first half of the sample period (1995-2002), but fail to detect statistically significant returns in the second half of the portfolio (2003-2010). However, the outperformance in the first half only exists when assuming small or moderate-sized transaction costs. Bajgrowicz and Scaillet (2012) used the false discovery rate in order to adjust for data snooping bias and applied this method to daily prices of the Dow Jones Industrial Average index from 1897 to 2011. They came to similar conclusions as the trading rules in their sample did not outperform the market index. Thus, based on the results of Park and Irwin (2007), Shynkevich (2011) and Bajgrowicz and Scaillet (2012), the performance of TA has declined over time. This suggests that the underlying aspects of the equity market have become more efficient during the past two decades.

More recent papers use sophisticated technology to account for data snooping biases and other limitations faced by earlier studies. Teixeira and Inacio de Oliveira (2010) examined whether an intelligent trading system based on TA techniques, in particular on data derived from asset prices and trade volume, is able to generate statistically significant profits. They found that their method yielded better results in comparison to a buy-and-hold strategy. Amongst other recent literature, Sezer et al. (2017) employed a deep neural-network-based trading system that optimises TA parameters and also arrived at the conclusion that their algorithms outperform the buy-and-hold strategy in terms of stock trading performance.

In contrast to studies that examined trading rules, we aim to circumvent data snooping bias by conducting event study analysis on analyst recommendations. Another advantage of employing analyst recommendations concerns the fact that technical trading rules may not cover the full spectrum of TA. According to Roscoe and Howorth (2009), chartists consist of two groups, namely trend-seekers (or “momentum” traders) and pattern-seekers. Trend-seekers try to identify stocks that are headed in a certain direction, whereas pattern-seekers aim to predict trend-reversals and price movements of stocks or other assets. As a consequence, next to quantitative techniques, TA also involves the recognition of certain patterns in the data by means of visually inspecting a time-series plot (Menkhoff and Taylor, 2007). In contrast to pure technical trading rules, technical analysts are likely to consider the visual and “gut feeling” aspects as well.

2.2. Technical analysis and investor behaviour

According to Menkhoff (2010), TA is more likely to be effective if security prices are influenced by non-fundamental factors that can be driven by general market mood and investors’ behavioural biases such as overconfidence or fear, which could eventually lead to stock market bubbles and their subsequent crashes. However, there is a striking absence of evidence on the exact strategies and behaviour of individual TA investors (Roscoe & Howorth, 2009). An important paper in this respect is the one from Barber and Odean (2002), who found that individual investors overtrade and that this has a detrimental effect on their performance. The authors argue that overtrading is the result of overconfidence. An interesting hypothesis would be that this underperformance found by Barber and Odean (2002) is explained by the fact that a relatively large number of individual investors employ TA. Related to this, Hoffmann and Shefrin (2014) illustrated that optimistic and overconfident investors seem to be more likely to use TA instead of fundamental analysis or an alternative strategy.

In contrast to the papers that solely cover the predictive abilities of technical trading rules, Lewellen, Lease and Schlarbaum (1980) and Hoffmann and Shefrin (2014) took into account the behavioural aspect of TA by covering the linkage between TA and individual investors. Particularly, Lewellen et al. (1980) found that TA damages the portfolios of individual investors substantially. However, they used data from the period between 1964 and 1970. Given that technology and other innovations have advanced over the years, these results may not be representative anymore. Nowadays, all investors can easily access platforms or services that provide a large selection of TA indicators and related tools. Therefore, one can resort to Hoffmann and Shefrin (2014), who used data from the period 2000-2006 and compare the returns of traders who use TA to the returns of traders who use fundamental analysis. Their main findings indicate that investors who use technical indicators earn lower returns, are more likely to speculate, trade more frequently, hold more concentrated portfolios and have a higher exposure to non-systematic risk. As a result, technicians are likely to incur relatively high transaction costs.

2.3. Technical analyst recommendations

As a substantial portion of research has provided evidence to the detriment of TA, some technical analysts responded to the criticism by claiming that the eminence of TA may not lie in stringently implementing technical trading rules, but rather in synthesising multiple signals into one recommendation (e.g. Dawson, 1985; Gerritsen, 2016), as well as considering the visual aspect of TA and gut feeling (Roscoe & Howorth, 2009). This implies that TA-based recommendations may provide a more accurate picture of the merit of TA than trading rules, suggesting that the focus of academic research should shift towards recommendations issued by technical analysts. Notably, existing research investigated recommendations from technical analysts only sporadically. Among the researchers who examined technical recommendations, Cowles (1933) was the first to explore it. He examined 255 recommendations, which were issued by the editors of the Wall Street Journal at that time and encompassed the Dow Jones Industrial Average (DJIA). They based their recommendations on the Dow Theory (Murphy, 1999), which forms the basis of the most important principles of TA by analysing maximum and minimum market fluctuations to make accurate predictions on the direction of the market. Covering a period of 26 years, following their recommendations would have resulted in a 12% average annual rate of return, whereas the DJIA increased 15.5% per year in the same period. Cowles (1933) applied the same methodology to the Dow Jones Railroad Average and obtained similar results. Therefore, his findings suggest that the buy-and-hold strategy was more profitable than pursuing TA-based recommendations. Brown et al. (1998) utilised the same dataset and analysis as

Cowles (1933) while taking risk into account. In contrast to Cowles (1933), they found that the DJIA underperformed the technical recommendations after controlling for risk.

Dawson (1985) was the first to consider recommended shares instead of recommended indices. He evaluated 292 round-trip TA-based stock recommendations published by a Singapore investment advisory firm. A round-trip in this case entails that the position taking after every buy recommendation will close after a certain holding period. He found that pursuing a strategy based on the recommendations did not yield abnormal returns while also accounting for transaction costs. More recently, Gerritsen (2016) examined short-term returns surrounding technical recommendations using a dataset that contains 5017 analyst recommendations for Dutch shares and indices between 2004 and 2010. His main finding is that these recommendations do not lead to significant abnormal returns and that the recommendations are correlated to the most common technical trading rules. As a consequence, he concluded that chartists do not have abilities beyond simply relying on technical indicators. In addition, buy recommendations tended to be issued after a period of positive abnormal returns and stop-loss levels did not contain informational value.

2.4. Fundamental analysis and technical analysis

A substantial portion of investors and traders use both fundamental and technical analysis (Taylor & Allen, 1992). In contrast to technical analysts, fundamental analysts aim to determine the intrinsic value of an investment instrument, which is derived from the performance of the particular company and the economy in general (Lam, 2004). This approach utilises quantitative tools such as financial ratios compiled from financial statements as well as qualitative indicators, such as marketing strategy, management policy, and product innovation.

Although the technical and fundamental analysis works of literature invest considerable effort in assessing their respective ability to predict future share prices, in general, they do so without reference to each other. Only a few papers investigated the complementary nature of TA and FA. Lam (2004) integrated TA and FA for financial performance prediction by means of neural networks and showed that these neural networks outperformed the overall average market return, namely the S&P 500, between 1985 and 1995. Eiamkanitchat et al. (2016) used the multilayer perceptron neural network in order to reveal the most favourable FA and TA techniques and applied these on stocks listed on the Stock Exchange of Thailand in 2015. Notably, the most favourable TA technique is the exponential moving average. Based on their experiment, the simulated portfolios obtained returns that are almost three times higher than the average market yield. Jamali and Yamani (2019) examined whether trading strategies based on both TA and FA are able to forecast emerging market currencies. They found that the combination of the best performing models exhibit superior predictive accuracy and produce substantial risk-adjusted and net-of-transaction costs returns. They stated that the symmetric Taylor rule is the best FA method and the momentum indicator is statistically superior to other technical indicators. These findings suggest that employing both TA and FA may be the optimal strategy.

Many brokers and broker-dealers issue stock recommendations that are based on fundamental analysis conducted by analysts from their research department. Commonly, these analysts assign “buy’’, “hold” or “sell” ratings to particular stocks. The quality of the analyst reports has a direct influence on how clients and investors perceive the brokerage firms, which, as a result, affects the size and satisfaction of their client base (Chung, 2000; Ribstein, 2005; Teoh & Wong, 2002). A substantial portion of both professional and retail investors rely on the recommendations published by large brokerage firms when evaluating the future performance of potential firms (Cornell, 2001). According to Brody and Rees (1996), the desire of investors to invest in firms that outperform the market and the confidence they have in the forecasting skills of security analysts underly the fact that many of them consider or follow recommendations from fundamental analysts. As a consequence, the market for analyst recommendations is enormous. The confidence investors have in analysts comes from the belief that they contribute to the price discovery of stocks by assembling and processing complex information derived from financial statements, industry-level competitive dynamics and macro-economic factors (Wang, 2009). Sell-side security analysts have a particularly large influence on retail investors as these typically unsophisticated investors do not have the required financial literacy and therefore tend to blindly follow investment advice from equity analysts (Damodaran, 2003). Given the large group of retail investors that base their investment decisions on the recommendations from brokers, as well as the potential conflict of interest between brokers and their clients, analyst reports have drawn the attention of regulators (Mikhail, Walther and Willis, 2004). In terms of legislation, the most important change in regulations concerns the approval of the Sarbanes-Oxley Act in 2002, which, amongst others, aimed at establishing a separation between the remuneration of equity analysts and in-house revenues related to investment banking activities such as trading and underwriting (Ebinger, 2008).

Recent research regarding the veracity of fundamental recommendations suggests that analysts fail to outperform the market on a consistent basis (e.g. Barber et al., 2001, 2003). Moreover, Baker and Dumont (2014) concluded that stocks with “buy” ratings consistently underperform equities with “hold” ratings. The authors argue that this finding could imply that analysts may have the intention to mislead investors. These findings suggest that analysts who use fundamental information simply fail to accurately predict the intrinsic value of stocks, or that the incentives of broker-analysts are not in alignment with the interests of investors who use the analyst reports. With regard to the latter, principal-agency problems may lead brokerage firms to recommend stocks that benefit them but not investors who rely on reports that are supposedly objective. Considering agency theory and in particular information asymmetry, the research departments of brokers could have an incentive to assign too positive recommendation ratings to current and potential future (investment banking) clients in order to retain and attract clients, which would, in turn, lead to higher revenues for the brokers on the detriment of retail investors that follow their advice. In fact, Michealy and Womack (1999) found that analysts suffer from incentive and heuristic-based biases, which adds to the concerns surrounding the intentions of analysts who publish reports on behalf of broker-dealers.

In contrast to the studies that find a negative association between buy-recommendations based on fundamental analysis and abnormal returns, Gerritsen and Lötter (2015) showed that recommended stocks with the highest ratings are associated with significant and positive abnormal returns in the short term. Their results are based on recommendations on companies listed on the Johannesburg Stock Exchange between 1995 and 2011.

2.5 Hypothesis development

Since existing research that focuses on the relationship between TA-based recommendations and returns is sparse, this paper aims to contribute to the current literature by evaluating the (abnormal) returns surrounding technical recommendations by means of event study analysis using recent data and equities that are listed in different countries, and by comparing the results for various asset types. The forecasting abilities of technical analysts can be measured in both absolute and relive terms. The former relates to market timing, while the latter involves identifying equities that outperform the market in a certain time period (Gerritsen, 2016). In the event that technical analysts have particular market timing skills, following buy recommendations should lead to positive raw returns. In case technicians are able to outperform by means of obtaining risk-adjusted returns, recommendations should be followed by positive abnormal returns. Since the performance of TA-based recommended assets could relate to either absolute or relative price patterns, the analyses include both raw and abnormal returns. However, the main focus of this paper concerns abnormal returns as this analysis takes risk factors into account and thus provides more meaningful insights.

Given weak-form market efficiency (Fama, 1965), the fact that Cowles (1933), Dawson (1985) and Gerritsen (2016) failed to identify a positive association between TA recommendations and returns, that some papers found that the profitability of TA has diminished over time (e.g. Shynkevich, 2011), and because many papers found that technical trading rules do not yield abnormal returns after adjusting for data snooping, we expect that employing TA-based recommendations does not lead to abnormal returns. Following the notion that investors predominantly use TA for short-term investment horizons (Menkhoff, 2010), the main hypothesis of this paper is:

H1: Following technical analyst recommendations is not related to statistically significant abnormal returns shortly after the recommendation.

The second analysis concerns the returns preceding recommendations. As TA solely uses past data, by definition, it builds on past price patterns. Only Bollinger bands and the Relative Strength Index are countertrend indicators (Park & Irwin, 2007). As a result, all other TA tools should follow the (short-term) trend and thus generate a buy signal if equities are in an upward trend. In addition, one of the main groups of technicians, in particular trend-seekers or "momentum" traders, select assets on the basis of their direction. In addition, Gerritsen (2016) found that upward and downward trends triggered buy and sell recommendations, respectively. As a consequence, we expect buy recommendations to follow a period of positive price patterns, resulting in positive abnormal returns during the pre-recommendation period. This leads to the second hyphothesis:

H2: Buy recommendations follow a period of positive abnormal returns

No study has compared the profitability of these asset types using recommendations from technical analysts. However, according to Taylor (1992), a substantial portion of forex traders employ technical analysis. In addition, since some papers that examined the profitability of technical trading rules, including recent ones, such as Alanazi and Alanazi (2020), found that TA is more effective for forex compared to stocks, indices and commodities, the third hypothesis is:

H3: TA recommendations for forex lead to higher abnormal returns after the recommendation relative to stocks, indices and commodities.

Although some research exists concerning the predictive capabilities of technical and fundamental analyst recommendations in isolation, no consensus has been reached yet regarding their profitability with reference to each other. Current literature has not directly investigated the relative performance of TA-based recommendations and FA-based recommendations. In addition, since Hoffmann and Shefrin (2014) found that individual investors who use TA obtain lower returns than those who use fundamental analysis, the fourth hypothesis is:

H4: Abnormal returns following technical recommendations are higher than abnormal returns following fundamental recommendations.

3. Research Design

3.1. Sample selection

In terms of data retrieval, this research requires investment recommendations from technical analysts. BTAC Visual Analysis provided these data. The dataset consists of TA recommendations for stocks, major indices, forex and commodities for various countries and it covers the period between October 2016 and February 2021. Attached to their recommendations, they included notes about the rationale behind buy, sell or hold recommendations. Based on these notes, the technical analysts who provided the data considered technical trading rules as well as visual interpretations of price movements and trends. As a result, the TA-based recommendations in our sample comply with the exhaustive definition of TA. Appendix A provides a snapshot of what the recommendations look like. Although the technicians issued a few sell recommendations, these are not included in the analysis as the number of buy recommendations are much higher. In total, the technical analysts issued 413 buy recommendations during the particular period. Table 1 illustrates the number of buy recommendations for each asset class.

Table 1
This table shows the number of recommendations for the various asset classes in the sample.

Category	Total	Stocks	Indices	Commodities	Forex
Count	413	337	43	24	8

This dataset also contains the date on which the recommendations have been published, which is key for our analyses. In order to test the hypotheses, we collected the risk-free rate, the prices of the recommended European stocks, global indices, forex, and commodities in our dataset during the given period, as well as daily returns including reinvested dividends. Since the dataset consists mostly of European stocks, the 1-month Euribor rate is considered as the risk-free interest rate and the STOXX 600 as the market index. The stock prices, risk-free rate and returns are retrieved from Factset. In addition, the Fama/French 4 Research factors are collected from the Fama/French website. Finally, we collected the FA-based recommendations from guruwatch.nl, which is part of the IEX media group (see Appendix B). The dataset contains solely fundamental recommendations published by large investment banks, brokers or financial advisory firms, such as Goldman Sachs, JPMorgan Cazenove and Deutsche Bank.

3.2. Methodology

Current research examining the performance of TA benchmarks the returns of employing this strategy either to market returns, buy-and-hold returns or expected returns. We focus on the latter in order to take the amount of risk into account. Given that we aim to determine the determinants and profitability of TA, all hypotheses require the computation of abnormal returns in the 30-day period around the dates of the technical analyst recommendations in order to conduct event study analysis. These calculations and procedures are in accordance with Gerritsen (2016). Although the dataset contains a date for each recommendation, not all recommendations are issued with an exact time. As a result, those recommendations may be published after, before or during trading ours. For instance, technical analysts can base their recommendations on futures markets before trading of regular securities starts. Hence, the day on which a recommendation is published is part of the pre-recommendation period. Particularly, (-9,0) will be treated as the pre-recommendation period and (1,20) will serve as the post-recommendation period.

With regard to stocks, the first step is to assemble daily returns, including reinvested dividends, for each security in the sample. The next step involves the calculation of abnormal return for all securities, which is the difference between the realised excess return and the expected excess return for stock *i* on day *t* (equation 1).

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \tag{1}$$

As a result, these components need to be calculated first. The realised excess return is the difference between the raw stock return (including reinvested dividends) and the risk-free interest rate (equation 2), whereas the expected excess return is estimated based on the Fama-French-Carhart 4-factor model (equation 3).

$$R_{i,t} = r_{i,t} - r_{f,t} \tag{2}$$

Where $r_{i,t} = \frac{P_{i,t}}{P_{i,t-1}} - 1$

$$E\left(R_{i,t}\right) = \alpha_{i,t} + \beta_{1i,t}R_{m,t} + \beta_{2i,t}SMB_t + \beta_{3i,t}HML_t + \beta_{4i,t}MOM_t \tag{3}$$

Here, $E\left(R_{i,t}\right)$ is the expected excess return, namely $E(r_{i,t}) - r_{f,t}$. Also, note that $R_{m,t}$ is the realised excess return, $r_{m,t} - r_{f,t}$, on the STOXX 600 index, which is considered as the market return including reinvested dividends. In alignment with current research covering the profitability of TA, we use the Fama-French-Carhart 4-factor model in order to adjust for the risk level. In accordance with Fama and French (1993), SMB_t relates to the size effect (small minus big in terms of market capitalisation) and HML_t refers to the book value effect (high minus low with respect to the book-to-market ratio). MOM is an additional factor (Fama and French, 1997) pertaining to momentum and concerns the magnitude and sign of returns in the past year. The alpha and beta coefficients in the expected return regression (equation 3) are measured based on the 260 trading days prior to the recommendation day.

Concerning recommendations on indices, commodities and forex, the process of calculating abnormal returns is identical to the one for stocks, except for the computation of expected returns. Particularly, for these asset classes, the expected return is equal to the mean-adjusted excess return, using the period of 250 days preceding the pre-recommendation period (equation 4).

$$E\left(R_{i,t}\right) = \frac{1}{250} \times \sum_{-10}^{-260} R_{i,t} \tag{4}$$

Where $R_{i,t} = r_{i,t} - r_{f,t}$

The next step concerns estimating the average abnormal returns (AAR) for each trading day in the pre-recommendation period and the post-recommendation period by taking the average of the abnormal returns for each event day (equation 5). Since the days surrounding recommendations are event days in this case and not calendar days, these days refer to *t'*.

$$AAR_{t'} = \frac{1}{N_{t'}} \sum_{i=1}^{N_{t'}} AR_{i,t'} \tag{5}$$

Here, $N_{t'}$ is the number of recommendations at day *t'* and $AR_{i,t'}$ is the abnormal return for stock *i* on day *t'*. Next, we employ the following t-test in order to determine whether the calculated average abnormal returns are significantly different from zero (equation 6).

$$t - statistic_{t'} = \frac{AAR_{t'}}{S(AR)_{t'}/\sqrt{N_{t'}}} \tag{6}$$

Here, $S(AR)_{t'}$ refers to the estimate of the standard deviation of the average abnormal return. Afterwards, we calculate the cumulative average abnormal returns (CAAR) for various 5-day event windows by taking the sum of the AARs for each event window (equation 7) and test whether these cumulative values are significantly different from zero by means of a t-test (equation 8). Note that n' pertains to event windows.

$$CAAR_{n'} = \sum_{t'}^{T} AAR_{t'} \tag{7}$$

$$t - statistic_{n'} = \frac{CAAR_{n'}}{\frac{S(AR)_{n'}}{\sqrt{N}_{n'}} \times \sqrt{n}} \tag{8}$$

Here, *n* is the number of days in the event window. The six different 5-day event windows cover both the pre-recommendation period and the post-recommendation period, particularly (−9, −5), (−4, 0), (1, 5), (6, 10), (11, 15), and (16, 20).

With respect to fundamental recommendations, the procedure is identical to technical recommendations. In alignment with Metghalchi et al. (2008), we perform the following Independent Samples t-Test (equation 9) in order to compare the average abnormal returns surrounding both types of recommendations.

$$t - statistic_{t'} = \frac{AAR(TA)_{t'} - AAR(FA)_{t'}}{\sqrt{\frac{Var(TA)_{t'}}{N(TA)_{t'}} + \frac{Var(FA)_{t'}}{N(FA)_{t'}}}} \quad (9)$$

Here, $Var(TA)_{t'}$ and $Var(FA)_{t'}$ represent the variance of TA-based and FA-based recommended abnormal stock returns on event day t', respectively. $N(TA)_{t'}$ refers to the number of technically recommended stocks and $N(FA)_{t'}$ to the number of fundamentally recommended equities.

4. Data Analysis and Results

4.1. Abnormal returns following recommendations from technical analysts

Answering Hypotheses 1 and 3 requires an analysis of the abnormal returns in the post-recommendation period (1, 20). Panel A of Table 2 illustrates the average raw and abnormal returns of all asset classes in the sample for the five days after publications of TA-based recommendations. With regard to stocks, most values are statistically significant at the 0.1% level. Both ARR and AAR are negative the first day after the publication and positive the second, fourth and fifth day after the recommendation. However, the returns on these event days are less pronounced in terms of economic significance as they are relatively small in size. On the other hand, the cumulative average raw and abnormal stock returns, which are shown in

Table 2

Abnormal and raw returns following TA-based recommendations. This table shows the returns after buy recommendations have been issued for all asset classes in the sample. Note: ***, **, and * denote significance levels of 0.1%, 1%, and 5%, respectively, for the test statistic.

Panel A: average raw returns (ARR) and average abnormal returns (AAR) in the 5 days following recommendations

Day	Recommendations							
	Stocks		Indices		Commodities		Forex	
	ARR	AAR	ARR	AAR	ARR	AAR	ARR	AAR
1	−0.24%***	−0.41%***	0.18%***	0.15%***	−0.13%	−0.15%*	0.09%	0.10%
	(−11.65)	(-20,43)	(6.70)	(5.69)	(−1.94)	(−2.04)	(1.51)	(1.71)
2	0.37%***	0.34%***	−0.17%***	−0.20%***	0.10%	0.07%	0.07%	0.08%
	(18.16)	(17,10)	(−6.46)	(−7.47)	(1.50)	(0.99)	(1.12)	(1.30)
3	−0.07%***	−0.02%	−0.20%***	−0.22%***	0.20%**	0.17%*	0.15%*	0.16%*
	(−3.57)	(−0,76)	(−7.43)	(−8.44)	(3.06)	(2.37)	(2.40)	(2.61)
4	0.11%***	0.20%***	0.02%	−0.01%	−0.31%***	−0.33%***	0.04%	0.05%
	(5.50)	(10.10)	(0.60)	(−0.40)	(−4.75)	(−4.55)	(0.65)	(0.83)
5	0.14%***	0.12%***	0.10%***	0.08%**	−0.55%***	−0.58%***	−0.06%	−0.05%
	(6.66)	(6.27)	(3.82)	(2.81)	(−8.52)	(−7.88)	(−1.00)	(−0.85)

Panel B: cumulative average raw returns (CARR) and cumulative average abnormal returns (CAAR) in four 5-day intervals following recommendations

Period	Recommendations							
	Stocks		Indices		Commodities		Forex	
	CARR	CAAR	CARR	CAAR	CARR	CAAR	CARR	CAAR
(1, 5)	0.31%***	0.24%***	−0.07%	−0.21***	−0.69%***	−0.81%***	0.28%	0.34%*
	(6.75)	(5.49)	(−1.24)	(−3.48)	(−4.76)	(−4.96)	(2.09)	(2.51)
(6, 10)	1.47%***	1.25%***	−0.04%	−0.18%**	−0.61%***	−0.73%***	−0.07%	−0.02%
	(32.09)	(28.12)	(−0.72)	(−2.97)	(−4.20)	(−4.47)	(−0.54)	(−0.17)
(11, 15)	0.35%***	0.035%	0.12%*	−0.01%	−2.66%***	−2.79%***	0.46%**	0.51%**
	(7.66)	(0.78)	(2.05)	(−0.20)	(−18.33)	(−16.99)	(3.36)	(3.80)
(16, 20)	−0.31%***	−0.48%***	−0.01%	−0.15%**	1.02%***	0.90%***	0.07%	0.12%
	(−6.67)	(−10.79)	(−0.23)	(−2.48)	(7.00)	(5.46)	(0.53)	(0.92)

Panel B of Table 2, are positive and statistically and economically significant for the second week after a recommendation (1.47% and 1.25%, respectively). The CAARs are also positive and statistically significant in the first and third week, but these are less salient in terms of economic significance.

With respect to indices, the AARs are negative and statistically significant at the 0.1% level on days two and three. On the first and fifth day, the AARs are positive and significant. Interestingly, the CAARs are negative during the whole post-recommendation period, yielding significant abnormal returns in statistical terms except for the third trading week. The ARRs and CARRs are similar to their abnormal counterparts, except for the CARRs that relate to the third trading week as these are positive and slightly significant.

Concerning commodities, the only statistically significant positive AAR relates to the third trading day after recommendations. Given that the returns are low in magnitude, their economic relevance is lower compared to stocks. However, the findings are in accordance with the notion that indices are less volatile than stocks. The AARs of commodities are slightly significant and negative on the first, fourth and fifth day after a recommendation, and the same applies to the CAARs during the first two weeks. The third week is more interesting, as both the CAAR (-2.79%) and t-value are high in magnitude. Again, the findings are comparable to the ARRs and CARRs. Finally, the raw and abnormal returns are less pronounced for forex, since the findings are small and only slightly significant on the third day and during the first and third week. These values have a positive sign, but the insignificance of the other days and weeks demand discretion.

Since the results are different for each asset type, answering the first hypothesis requires separate analyses. Although the abnormal returns of stocks are relatively ambiguous the first week after a recommendation, they are substantial during the second week. Regarding indices, the abnormal returns are mainly negative throughout the full post-recommendation period. For commodities, abnormal returns are negative during the first three weeks, while the fourth week yields positive results. Adhering to technical recommendations that concern forex does not lead to notable abnormal returns, except for the third week. Therefore, with regard to Hypothesis 1, we conclude that TA-based recommended stocks seem to yield risk-adjusted returns in the short term. On the contrary, following TA-based recommendations has an adverse effect on the short term abnormal returns of indices and commodities. Particularly recommendations from technical analysts that concern commodities should be avoided during the first few weeks after the recommendation. Remarkably, recommended commodities tend to yield positive abnormal returns after three weeks. Overall, in the case of indices and commodities, we reject Hypothesis 1. Although the abnormal returns of recommended forex are positive and moderate in size during the third week, the abnormal returns in the previous weeks are small and hardly significant. As described in the limitations section, the low number of forex recommendations could explain the relatively insignificant findings. Thus, Hypothesis 1 cannot be rejected in the case of forex.

With respect to Hypothesis 3, the results vary among the different asset classes. The predictions of technical analysts seem to be most accurate for stocks, whereas TA does not seem to be a reliable investment strategy for indices and commodities. Given that forex recommendations lead to lower and less significant abnormal returns relative to stocks, Hypothesis 3 should be rejected.

4.2. Abnormal returns prior to recommendations from technical analysts

Hypothesis 2 requires an analysis involving abnormal returns in the pre-recommendation period (-9, 0). Panel B of Table 3 shows that the CARR and CAAR of stocks and commodities are substantial, positive and accompanied by very high t-values for the (-4, 0) period. As shown in Panel A of Table 3, these findings are mainly explained by considerable ARRs and AARs on the day of the recommendation (event day 0). The ARRs and AARs of commodities as well as their concomitant t-values are also significant on the day before a recommendation, while the results are mixed for the preceding days. On event days -4, -3 and -2, AARs are significantly negative in the case of indices. However, equivalently to stocks and commodities, AARs are statistically positive on the event day itself as well as the preceding day. Specifically, on the publication day, the AARs of stocks, indices and commodities are 1.42%, 0.30% and 1.53%, respectively. Due to the return reversal that takes place within the (-4, 0) event window, the indices CAAR of this particular week is insignificant as the positive and negative returns

Table 3

Abnormal and raw returns prior to TA-based recommendations. This table shows the returns before buy recommendations have been issued for all asset classes in the sample. Note: ***, **, and * denote significance levels of 0.1%, 1%, and 5%, respectively, for the test statistic.

Panel A: average raw returns (ARR) and average abnormal returns (AAR) in the 5 days prior to recommendations

Day	Recommendations							
	Stocks		Indices		Commodities		Forex	
	ARR	AAR	ARR	AAR	ARR	AAR	ARR	AAR
−4	0.16%***	0.09%***	−0.14%***	−0.17%***	−1.07%***	−1.09%***	0.14%*	0.15%*
	(7.77)	(4.30)	(−5.42)	(−6.42)	(−16.43)	(−14.89)	(2.26)	(2.47)
−3	0.16%***	0.20%***	−0.15%***	−0.17%***	−0.18%**	−0.21%**	−0.13%*	−0.12%*
	(7.88)	(9.93)	(−5.54)	(6.54)	(−2.83)	(−2.84)	(−2.20)	(−2.07)
−2	−0.28%***	−0.37%***	−0.18%**	−0.21%***	0.53%***	0.51%***	0.09%	0.10%
	(−13.64)	(−18.79)	(−6.70)	(−7.70)	(8.23)	(6.95)	(1.48)	(1.67)
−1	0.43%***	0.17%***	0.23%***	0.20%***	1.51%***	1.48%***	−0.06%	−0.05%
	(21.04)	(8.46)	(8.61)	(7.61)	(23.17)	(20.19)	(−0.98)	(−0.83)
0	2.12%***	1.42%***	0.33%***	0.30%***	1.55%***	1.53%***	−0.37%***	−0.36%***
	(103.67)	(71.11)	(12.41)	(11.40)	(23.90)	(20.84)	(−6.14)	(−6.08)

Panel B: cumulative average raw returns (CARR) and cumulative average abnormal returns (CAAR) in two 5-day intervals prior to recommendations

Period	Recommendations							
	Stocks		Indices		Commodities		Forex	
	CARR	CAAR	CARR	CAAR	CARR	CAAR	CARR	CAAR
(−9, −5)	−1.56%***	−1.66%***	0.20%***	0.06%	−1.48%***	−1.60%***	0.74%***	0.79%***
	(−34.03)	(−37.36)	(3.33)	(1.09)	(−10.19)	(−9.77)	(5.46)	(5.94)
(−4, 0)	2.59%***	1.49%***	0.09%	−0.04%	2.34%***	2.22%***	−0.34%*	−0.29%*
	(56.67)	(33.55)	(1.50)	(−0.74)	(16.12)	(13.53)	(−2.50)	(−2.16)

cross each other out. With respect to forex, the ARRs and AARs during the days up to the recommendation date are negligible, while these are rather negative on the recommendation day itself. The CARRs and CAARs of stocks, commodities and Forex are both economically and statistically significant in the (-9, -5) period, but vary in terms of their signs. In particular, stocks and commodities show a negative sign in this period (-1.66% and -1.60%, respectively), whereas the results are positive for forex (0.79%) and the CAAR is insignificantly positive for indices. Overall, the results suggest that TA-based recommendations on stocks, indices and commodities follow positive and sizable abnormal returns, particularly on event days 0 and -1. This matches the notion that most TA-based strategies are trend-following. Therefore, Hypothesis 2 cannot be rejected if one considers these asset types. However, this is not the case for forex as forex recommendations do not follow positive abnormal returns during the preceding days.

4.3. Return comparison between TA and FA

Given that fundamental analysis is the main counterpart of technical analysis when considering investment strategies, in this section we compare the returns following and preceding technical recommendations to returns surrounding fundamental recommendations. The FA-based recommended stocks are identical to the TA-based recommended stocks. Therefore, the only difference concerns the timing of recommendations, which minimises unobserved heterogeneity. This allows us to directly compare the performance of technical and fundamental analysts. Table 4 shows the abnormal and raw returns for the days and weeks surrounding both TA-based and FA-based recommendations, as well as their differences. Panel A illustrates that all fundamental AARs are statistically significant, except for the day before the recommendation day. Except for event day -4, all other AARs obtained during the days in the pre-recommendation period are positive. As a logical consequence, the fundamental CAAR (Panel B) is significant at the 0.1% level and relatively substantial (0.52%) in the trading week before the recommendation (−4, 0). The second week before FA-based recommendations, period (−9, −4), also yields a significant and positive CAAR (0.28%) but is less pronounced. Interestingly, the recommendation day serves as a turning point as all fundamental AARs on the few days following recommendations are significantly negative.

Subsequently, the fundamental CAAR that corresponds to the first week after recommendations is strongly negative and accompanied by a high t-statistic (−1.25% and −18.35, respectively). This negative trend continues throughout the second week, but the third and fourth-week fundamental CAARs are positive. However, these values are less distinctive in terms of significance and magnitude compared to the first week succeeding a recommendation. The fundamental ARRs and CARRs are comparable to their absolute equivalents in terms of their signs, except for the (1, 5) event window. These results indicate that the risk-adjusted returns are eminently negative during the first days after recommendations are published. Given that the abnormal returns tend to be significantly higher than zero during the two trading weeks before the event day, FA-based recommendations seem to follow the medium-term trend. Also, the results suggest that following this type of recommendations has an adverse effect on returns during the first few days but a reversal takes place during the second trading week, which lasts at least up to the fourth trading week.

The last column of Panel A of Table 4 presents the difference between technical and fundamental AARs. The most compelling result concerns the recommendation day itself since the technical AAR is 1.19

Table 4

Abnormal and raw returns surrounding both TA-based and FA-based recommendations. This table shows the returns after buy recommendations have been issued for all asset classes in the sample, as well as the difference between technical and fundamental returns based on an Independent Samples t-Test. Note: ***, **, and * denote significance levels of 0.1%, 1%, and 5%, respectively, for the test statistic.

Panel A: average raw returns (ARR) and average abnormal returns (AAR) in the 10 days surrounding recommendations and the difference between TA and FA returns.

Day	Recommendations					
	Raw		Abnormal		Δ	
	ARR_{TA}	ARR_{FA}	AAR_{TA}	AAR_{FA}	$ARR_{TA\text{-}FA}$	$AAR_{TA\text{-}FA}$
−4	0.16%***	−0.052%	0.36%***	−0.13%***	0.21%***	0.21%***
	(7.77)	(−1.20)	(4.30)	(−4.12)	(4.40)	(5.80)
−3	0.16%***	0.16%**	0.20%***	0.13%***	−0.00%	0.07%*
	(7.88)	(3.73)	(9.93)	(4.08)	(−0.01)	(2.03)
−2	−0.28%***	0.58%***	−0.37%***	0.25%***	−0.86%***	−0.62%***
	(−13.64)	(13.32)	(−18.79)	(8.17)	(−17.86)	(−17.13)
−1	0.43%***	−0.02%	0.17%***	0.05%	0.45%***	0.12%**
	(21.04)	(−0.42)	(8.46)	(1.72)	(9.34)	(3.19)
0	2.12%***	0.32%***	1.42%***	0.23%***	1.80%***	1.19%***
	(103.67)	(7.44)	(71.11)	(7.40)	(37.45)	(32.75)
1	−0.24%***	−0.20%***	−0.41***	−0.26%***	−0.04%	−0.15%***
	(−11.65)	(−4.55)	(−20.43)	(−8.58)	(−0.85)	(−4.01)
2	0.37%***	0.65%***	0.34%***	−0.29%***	−0.27%***	0.63%***
	(18.16)	(14.87)	(17,10)	(−9.48)	(−5.71)	(17.29)
3	−0.07%***	0.22%***	−0.02%	−0.18%***	−0.29%***	0.17%***
	(−3.57)	(5.00)	(−0,76)	(−5.95)	(−6.04)	(4.56)
4	0.11%***	−0.34%***	0.20%***	−0.39%***	0.45%***	0.59%***
	(5.50)	(−7.87)	(10.10)	(−12.91)	(9.46)	(16.33)
5	0.14%***	−0.06%	0.12%***	−0.13***	0.19%***	0.25%***
	(6.66)	(−1.29)	(6.27)	(−4.18)	(4.00)	(6.93)

Panel B: cumulative average raw returns (CARR) and cumulative average abnormal returns (CAAR) in six 5-day intervals and the difference between TA and FA returns

Period	Recommendations					
	Raw		Abnormal		Δ	
	$CARR_{TA}$	$CARR_{FA}$	$CAAR_{TA}$	$CAAR_{FA}$	$CARR_{TA\text{-}FA}$	$CAAR_{TA\text{-}FA}$
(−9, −4)	−1.56%***	1.04%***	−1.66%***	0.28%***	−2.59%***	−1.95%***
	(−34.03)	(10.67)	(−37.36)	(4.17)	(−24.16)	(−23.95)
(−4, 0)	2.59%***	0.99%***	1.49%***	0.52%***	1.60%***	0.97%***
	(56.67)	(10.23)	(33.55)	(7.72)	(14.90)	(11.92)
(1, 5)	0.31%***	0.27%**	0.24%***	−1.25%***	0.04%	1.49%***
	(6.75)	(2.76)	(5.49)	(−18.37)	(0.38)	(18.38)
(6, 10)	1.47%***	0.53%***	1.25%***	−0.14%*	0.94%***	1.39%***
	(32.09)	(5.48)	(28.12)	(−2.04)	(8.71)	(17.10)
(11, 15)	0.35%***	1.11%***	0.035%	0.27%***	−0.76%***	−0.24%**
	(7.66)	(11.38)	(0.78)	(3.98)	(−7.04)	(−2.90)
(16, 20)	−0.31%***	1.64%***	−0.48%***	0.20%**	−1.95%***	−0.68%***
	(−6.67)	(16.92)	(−10.79)	(2.90)	(−18.15)	(5.46)

percentage points higher than the fundamental AAR and yields a much higher t-statistic compared to the other event days. Notably, the returns on the publication day are much less pronounced for fundamental recommendations compared to technical recommendations. With regard to event window (-4, 5), fundamental AARs only outperform technical AARs on event days -2 and 1, and the AARs do not differ much on event days -3 and -1. In terms of trading weeks, Panel B of Table 4 shows that fundamental CAARs are significantly higher than their technical peers for event windows (-9, -4), (11, 15) and (16, 20). However, technical CAARs clearly outperform in the weeks that fall in between. This implies that technical CAARs are higher than fundamental ones as long as it concerns a period that is relatively close to the recommendation date. The results are fairly similar for raw returns. Thus, considering Hypothesis 4, TA-based recommendations outperform FA-based recommendations during the first and second trading week after a recommendation has been published, whereas it underperforms during the third and fourth trading weeks.

5. Discussion

5.1. Profitability of technical analysis recommendations

In order to connect the results presented in the precious section, Figure 1 displays the

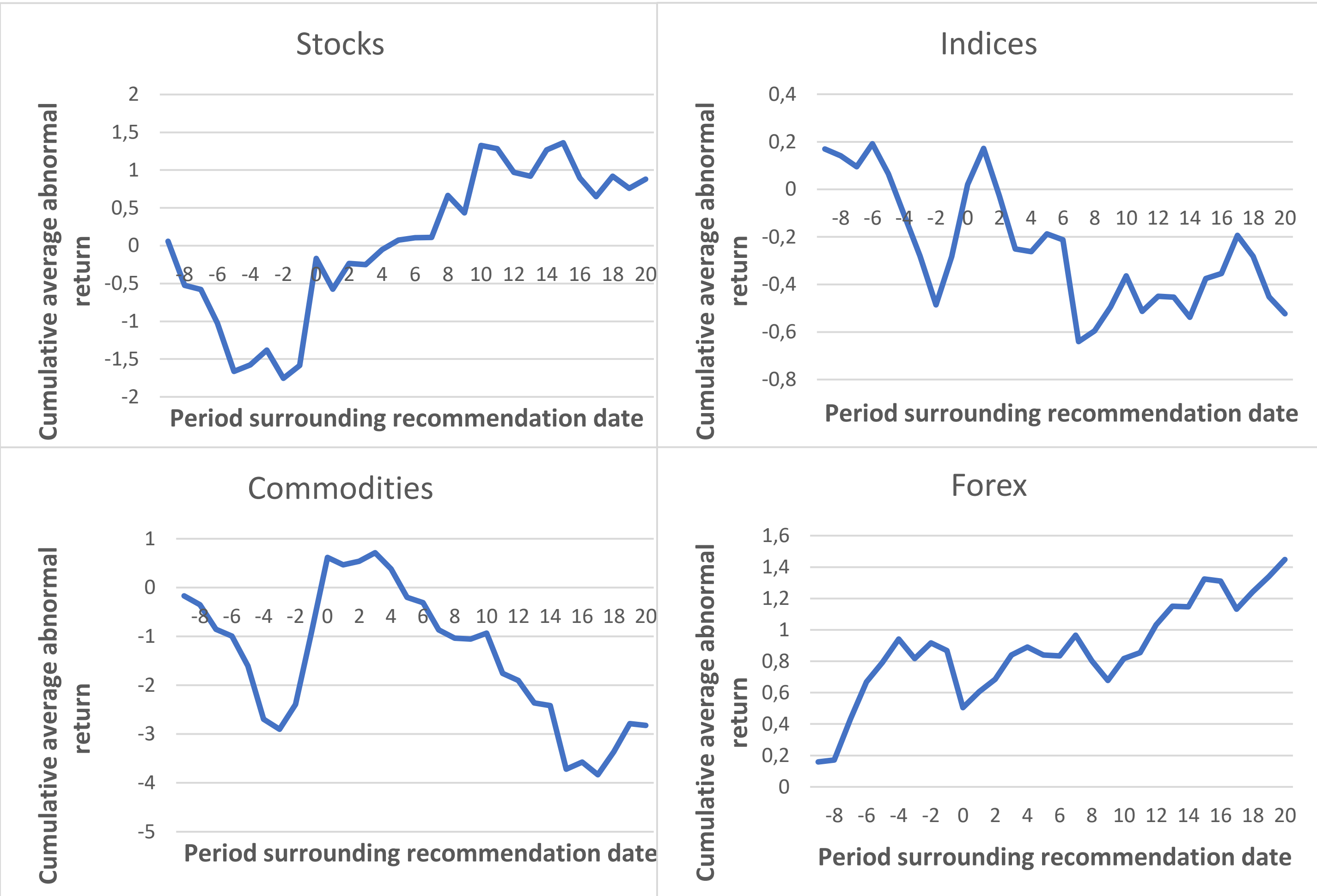

Figure 1. This figure illustrates the CAARs in the event period (-9, 20) for all asset classes in the sample.

cumulative average abnormal returns both before and after the date on which a recommendation has been published. As it concerns both the pre-recommendation and the post-recommendation periods, this figure practically combines the findings stated in Table 2 and Table 3. According to the Stocks Panel of Figure 1, the abnormal returns strongly declined up to two days before the recommendation date but then reversed right before and on the day of the recommendation. The abnormal returns continued to increase the next two weeks but consolidated the last two weeks of the post-recommendation period. Overall, it seems to be profitable to follow TA-based stock recommendations.

The Indices Panel shows that, after a significant decline at the beginning of the pre-recommendation period, the abnormal returns recovered up to the event day. Notably, the abnormal returns show a clear downtrend during the first six trading days after the recommendation, after which they show some signs of recovery until event day 18. In addition, note that the abnormal returns of indices are much less volatile compared to their peers, which explains the small scale. Given that Gerritsen (2016) found that the abnormal returns of recommended stocks and indices are positive and significant during the days preceding recommendations, our results confirm this finding. However, Gerritsen (2016) failed to identify significant abnormal returns following stock or index recommendations, whereas we found several statistically and economically significant results regarding stocks.

The Commodities Panel illustrates that the abnormal returns of commodities follow a similar pattern as stocks and indices during the pre-recommendation period. However, contrary to stocks but similar to indices, the abnormal returns of commodities strongly decrease throughout the post-recommendation period. Therefore, with reference to indices and commodities, a trend reversal took place around the recommendation day. In particular, abnormal returns increased until the event day (0), but declined afterwards. Overall, patterns of stocks, indices and commodities suggest that technical analysts managed to identify a peak on and right before the event day itself. The fact that technical indicators are based on historical data, combined with the trend-seeking behaviour of many chartists, may explain this observation. Finally, the Forex Panel exhibits a steady increase in abnormal returns during the full period (-9, 20). Naturally, these results are in alignment with Tables 2 and 3.

Corresponding to the full post-recommendation period (1, 20), the CAARs of TA-based recommended stocks, indices, commodities and forex are 1.05%, -0.54%, -3.44% and 0.94%, respectively. Their respective t-statistics are 11.80, -9.12, -10.48 and 3.53, which implies that these values are statistically significant. Thus, adhering to TA-based recommendations and holding the asset throughout the full post-

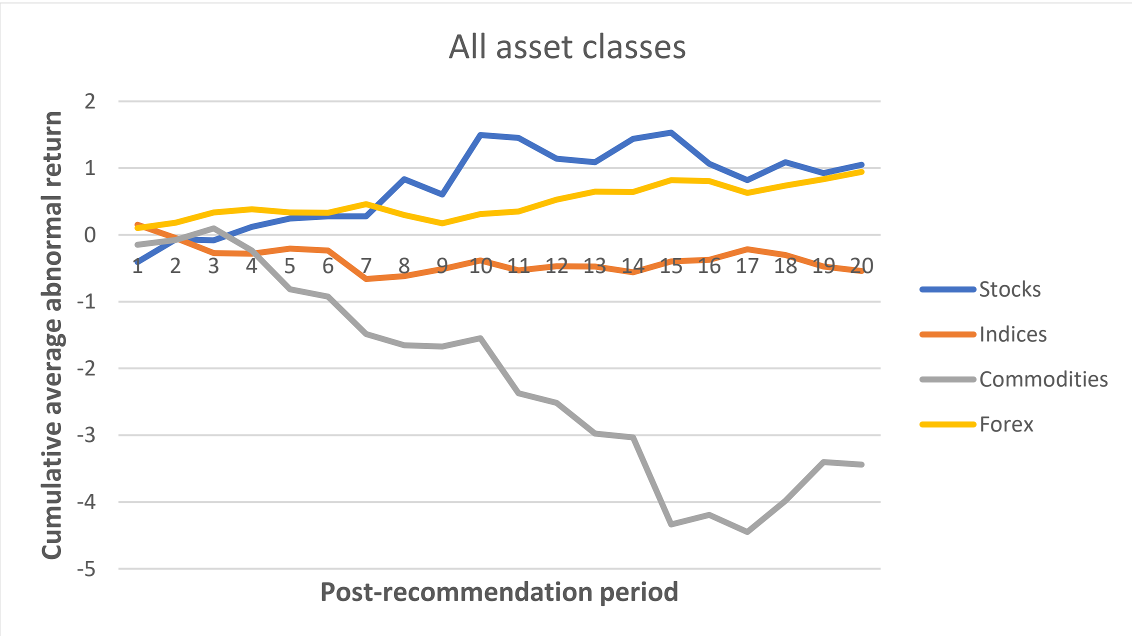

Figure 2. This figure illustrates the CAARs in the post-recommendation period (1, 20) for all asset classes

recommendation period yields positive abnormal returns in the case of stocks and forex, whereas this strategy earns negative returns if the recommendations concern indices and commodities. Figure 2 illustrates the performance of the various asset classes graphically.

Given that the technical analysts who provided the recommendations in the sample employed both technical trading rules and visual analysis, the findings indicate that TA is appropriate for analysing stocks and proves unsuitable for indices and commodities. The implications for forex are uncertain as the abnormal returns obtained in the recommendation period are relatively insignificant. The notion that TA is more powerful when applied to assets that are subject to non-fundamental factors such as behavioural biases (Menkhoff, 2010) may explain the outcomes of our analysis. Specifically, the outperformance of technically recommended stocks relative to their peers implies that investors are more prone to these non-fundamental factors when considering equities.

5.2. Comparison between technical and fundamental recommendations

Figure 3 presents Table 4 in a graphical way in order to identify patterns over time as it shows both technical and fundamental CAARs that fall in the pre-recommendation and post- recommendation periods. In fact, this figure represents the stocks Panel of Figure 1, including fundamental CAARs for the sake of comparison purposes. From a graphical perspective, both

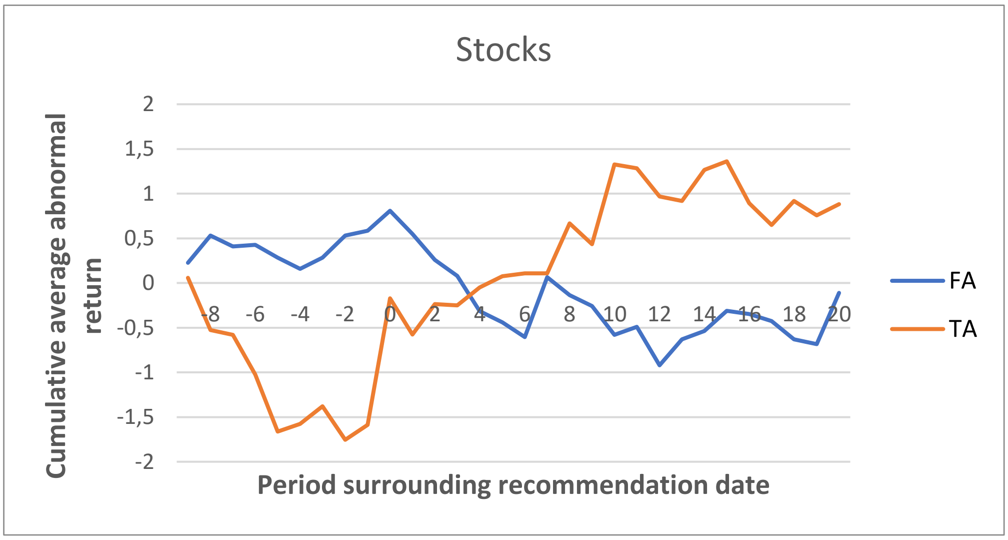

Figure 3. This figure illustrates TA and FA CAARs in the event period (-9, 20)

series of CAARs together create an X-shape. The patterns and implications of the technical CAARs have been discussed in the previous subsection, so this section focuses on fundamental CAARs and their differences. Figure 3 shows that abnormal returns steadily increased until the recommendation day, but strongly declined right after the publication of recommendations. However, the last two trading weeks show signs of recovery. This finding contradicts the results of Gerritsen and Lötter (2015), who found a positive association between fundamental recommendations and returns. On the other hand, this result is in accordance with

Barber et al. (2001, 2003) and Baker and Dumont (2014). In terms of their relative performance, fundamental abnormal returns are substantially higher than technical abnormal returns during the pre-recommendation period. Nonetheless, after the fourth day (the intersection point), technical abnormal returns increased drastically whereas fundamental abnormal returns declined, which leads to outperformance of technical recommendations during the (first part of the) post-recommendation period. Yet, FA-based recommendations slightly outperform TA-based recommendations towards the end of the event period. The fact that TA is generally used for short term investment horizons and FA for the long term could explain these findings.

In terms of the full post-recommendation period, the technical CAAR is 1.05% (t-statistic = 11.80) for the (1, 20) window and the fundamental CAAR is -0,92% (t-statistic = -6,77)

in the same period. Consequently, buying TA-based recommended stocks after the publication and holding them for four trading weeks on average yields a positive risk-adjusted return, while following the same

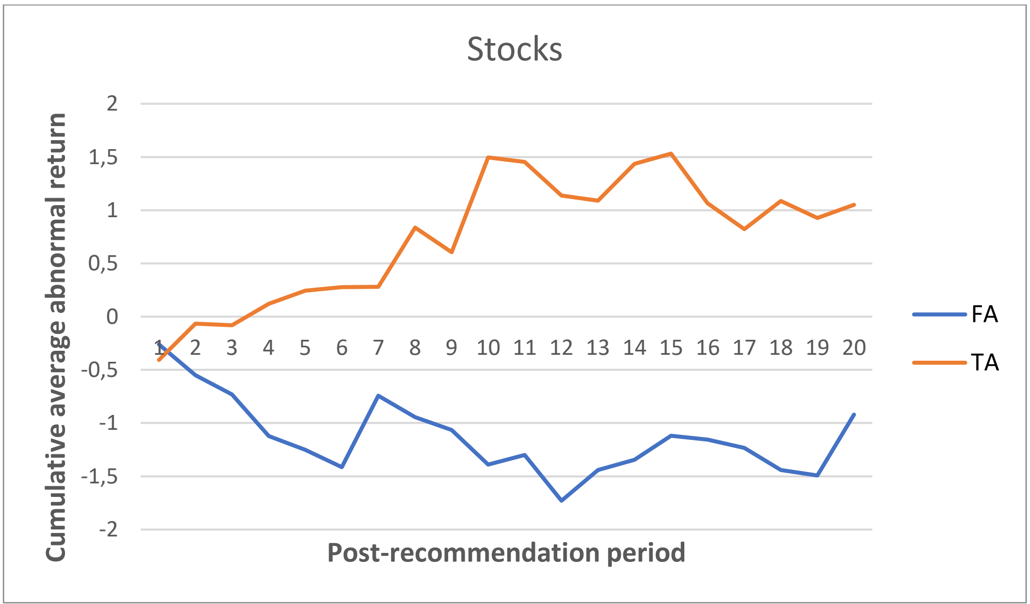

Figure 4. This figure illustrates TA and FA CAARs in the post-recommendation period (1, 20)

strategy yields negative risk-adjusted returns in the case of FA-based recommendations. Figure 4 shows this graphically since it reveals the performance of both FA and TA recommended stocks in terms of cumulative abnormal returns throughout the post-recommendation period.

5.3. Determinants of recommendations

One of the main findings concerns the fact that the abnormal returns of TA-based recommended stocks, indices, commodities and FA-based recommended stocks are positive and both economically and statistically significant regarding the trading week before the publication day of recommendations. The abnormal returns on the recommendation day itself are particularly high. Given that almost all technical trading rules, signals and indicators are based on historical data implies they are designed to follow the trend, while only a few TA tools lead to counter-trades. This may explain why TA-based recommendations tend to follow short-term abnormal returns. Additionally, the fact that abnormal returns of stocks, indices and commodities strongly decline up to the second day before the recommendation day and significantly rise right before recommendations implies that pattern-seekers are able to identify a short-term bottom.

However, the observation that abnormal returns of FA-based recommended stocks are positive before the recommendation and negative after the recommendation has different determinants relative to technical recommendations. In fact, FA-based recommendations are issued too late. As introduced in subsection 2.4, information asymmetry and conflict of interest could explain these results. In contrast to the technical analysts that issued the recommendations contained in the dataset, the fundamental analysts work for large investment banks and brokers. As a result, broker-dealers, where these fundamental analysts work, may have already reacted to the advice before it is made available to the public. This may relate to the potential inside information these firms have, which allows them to act on this information before they publish recommendations that are available to the general public.

A conflict of interest exists involving investment banks and (un)sophisticated investors who use analyst recommendations to base their investment decisions on. Firstly, investment banks have an incentive to issue unrealistically positive recommendations in order to avoid losing clients or foregoing the possibility to attract new clients in the future. Secondly, there is a positive correlation between the number of transactions and revenues. If brokers issue "hold" ratings, investors are less likely to make transactions than if brokers issue "buy" ratings. Accordingly, it is not surprising that the buy-sell ratio of the total recommendations in the dataset is eminent, even if the number of hold ratings is added to the number of sell ratings. Due to these reasons, the intrinsic value of a stock may be consistently lower than the value stated in a recommendation, leading to low or negative abnormal returns in the period after the recommendations.

6. Robustness tests

6.1. Generalised sign test

In order to validate the main results regarding the abnormal returns surrounding TA-based recommendations and gain more insights about them, we performed an additional test. The generalised sign test (Sanger & McConnell, 1986; Cowen & Sergeant, 1996) is a non-parametric test, which checks whether the number of positive abnormal returns on each day and week in the event period differs significantly from the number of positive abnormal returns in the period prior to the pre-recommendation period (-260, -10). The accompanying test statistic is defined as Equation 10.

$$GST - statistic_{t'} = \frac{|p_{t'} - p|}{\sqrt{p(1-p)/N_{t'}}} \quad (10)$$

Here, p specifies the portion of positive abnormal returns in the estimation period (-260, -10), which serves as the benchmark, and is calculated as the number of positive abnormal returns divided by the total number of positive and negative abnormal returns in the given period. Furthermore, $p_{t'}$ refers to the portion of positive abnormal returns on event day t'. Table 5 displays the results for the post-recommendation period. In the case of stocks, the reference percentage of positive abnormal returns is 48.7%. The only statistically significant result concerns the first day after the recommendation, where the number of positive abnormal returns is
lower than the benchmark. Indices and commodities with a buy recommendation underperformed the market on a risk-adjusted basis on the second and fifth day after the recommendation

Table 5

Generalised sign test on the returns following TA-based recommendations. (-260, -10) is referred to as the reference period. Note: ***, **, and * denote significance levels of 0.1%, 1%, and 5%, respectively, for the test statistic.

Panel A: GS-test applied to the 5 days following recommendations

Day	Recommendations							
	Stocks		Indices		Commodities		Forex	
	Raw	Abnormal	Raw	Abnormal	Raw	Abnormal	Raw	Abnormal
(−260, −10)	51.9%	48.7%	54.0%	52.3%	55.9%	52.4%	50.4%	51.4%
1	48.7%	43.3% *	63.6%	63.6%	50.0%	45.8%	75.0%	75.0%
	(1.19)	(1.97)	(1.28)	(1.51)	(0.58)	(0.64)	(1.39)	(1.34)
2	54.3%	51.3%	34.1%**	31.8%**	62.5%	58.3%	50.0%	50.0%
	(0.88)	(0.97)	(2.65)	(2.71)	(0.65)	(0.59)	(0.02)	(0.08)
3	44.5%**	46.0%	47.7%	47.7%	62.5%	62.5%	50.0%	50.0%
	(2.72)	(0.99)	(0.84)	(0.60)	(0.65)	(0.99)	(0.02)	(0.08)
4	45.4%*	45.7%	59.1%	56.8%	45.8%	41.7%	50.0%	62.5%
	(2.39)	(1.10)	(0.68)	(0.61)	(0.99)	(1.05)	(0.02)	(0.63)
5	47.8%	44.8%	61.4%	61.3%	29.2%**	33.3%*	37.5%	37.5%
	(1.52)	(1.43)	(0.98)	(1.21)	(2.64)	(1.87)	(0.73)	(0.79)

Panel B: GS-test applied to the four 5-day intervals following recommendations

Period	Recommendations							
	Stocks		Indices		Commodities		Forex	
	Raw	Abnormal	Raw	Abnormal	Raw	Abnormal	Raw	Abnormal
(−260, −10)	51.9%	48.7%	54.0%	52.3%	55.9%	52.4%	50.4%	51.4%
(1, 5)	48.1%	46.2%	53.2%	52.3%	50.0%	48.3%	52.5%	55.0%
	(1.39)	(0.90)	(0.11)	(0.00)	(0.58)	(0.39)	(0.12)	(0.20)
(6, 10)	52.8%	48.6%	56.8%	56.4%	58.3%	51.7%	40.0%	40.0%
	(0.33)	(0.03)	(0.37)	(0.55)	(0.24)	(0.07)	(0.59)	(0.64)
(11, 15)	53.2%	48.0%	54.5%	53.2%	55.0%	52.5%	55.0%	55.0%
	(0.49)	(0.25)	(0.07)	(0.12)	(0.09)	(0.01)	(0.26)	(0.20)
(16, 20)	51.9%	47.2%	53.6%	52.7%	62.5%	56.7%	52.5%	57.5%
	(0.01)	(0.56)	(0.05)	(0.06)	(0.65)	(0.42)	(0.12)	(0.35)

day, respectively. With regard to Forex and all CAARs of the various asset classes, the portion of positive returns is statistically insignificant.

Table 6 contains the results of the generalised sign test regarding the pre-recommendation period. Logically, the reference fractions of positive abnormal returns are the same as in Table 5. Recommended stocks underperform the market on event day -4 and event week (-9, -5), whereas they significantly outperformed the benchmark on the day before the recommendation and on the recommendation day itself. Recommended indices yielded a substantially higher portion of positive abnormal returns on the issuance day. The same applies to commod-

Table 6

Generalised sign test on the returns preceding TA-based recommendations. (-260, -10) is referred to as the reference period. Note: ***, **, and * denote significance levels of 0.1%, 1%, and 5%, respectively, for the test statistic.

Panel A: GS-test applied to the 5 days preceding recommendations

Day	Recommendations							
	Stocks		Indices		Commodities		Forex	
	Raw	Abnormal	Raw	Abnormal	Raw	Abnormal	Raw	Abnormal
(−260, −10)	51.9%	48.7%	54.0%	52.3%	55.9%	52.4%	50.4%	51.4%
−4	43.0%**	39.8%**	43.2%	43.2%	29.2%**	29.2%*	50.0%	62.5%
	(3.26)	(3.28)	(1.44)	(1.20)	(2.64)	(2.27)	(0.02)	(0.63)
−3	48.7%	46.6%	50.0%	47.7%	45.8%	41.7%	37.5%	37.5%
	(1.19)	(0.77)	(0.53)	(0.60)	(0.99)	(1.05)	(0.73)	(0.79)
−2	51.0%	45.4%	43.2%	40.9%	54.2%	54.2%	50.0%	50.0%
	(0.32)	(1.21)	(1.44)	(1.51)	(0.17)	(0.18)	(0.02)	(0.08)
−1	66.5%***	59.1%***	63.6%	65.9%	79.2%*	75.0%*	37.5%	50.0%
	(5.35)	(3.80)	(1.28)	(1.81)	(2.30)	(2.22)	(0.73)	(0.08)
0	75.7%***	66.2%***	70.5%*	70.5%*	75.0%*	70.8%	0.0%*	0.0%*
	(8.73)	(6.42)	(2.19)	(2.42)	(1.99)	(1.81)	(2.85)	(2.91)

Panel B: GS-test applied to the two 5-day intervals preceding recommendations

Period	Recommendations							
	Stocks		Indices		Commodities		Forex	
	Raw	Abnormal	Raw	Abnormal	Raw	Abnormal	Raw	Abnormal
(−260, −10)	51.9%	48.7%	54.0%	52.3%	55.9%	52.4%	50.4%	67.5%
(−9, −5)	46.4%*	41.8%**	54.1%	53.6%	46.7%	43.3%	65.0%	55.0%
	(2.04)	(2.54)	(0.01)	(0.18)	(0.91)	(0.89)	(0.83)	(0.91)
(−4, 0)	57.0%*	51.4%	54.1%	53.6%	56.7%	54.2%	35.0%	40.0%
	(1.96)	(0.99)	(0.01)	(0.18)	(0.08)	(0.18)	(0.87)	(0.64)

ities, but here it concerns the day before the day of publication. Interestingly, all forex recommendations were negative on the day of issuance.

All significant findings stated in Tables 5 and 6 are in alignment with those in Tables 2 and 3. Although most other results in Tables 5 and 6 are insignificant, they show similar directions compared to the results in Tables 2 and 3. The fact that observations arising from the generalised sign test are less significant than the results from the parametric test, implies that the magnitude of the abnormal returns on either positive or negative days is of larger relevance than the number of positive and negative abnormal returns.

6.2. Covid-19 stock market crash

In order to test whether the Covid-19 stock market crash does not distort the results, we replicated the main analysis, excluding recommendations that were published during and after March 2020. Tables 7 and 8 show the Covid-19 adjusted results.

The only noteworthy impact of pandemic concerns the CAAR of commodities in the

third trading week after the publication of recommendations. Here, the CAAR increases from -2.79% to -1.34%. However, the sign is still negative and the value is still significant in economic and statistical terms. Therefore, it does not influence the main analysis. In addition, the AAR of indices changed from -0.01% to 0.17% on the fourth day, which affects the first-week CAAR as a consequence. Overall, the abnormal returns and their concomitant t-statistics displayed by Tables 7 and 8 are almost identical to those in Tables 2 and 3. Thus, we conclude that the Covid-19 crash does not distort the main findings.

Table 7

Abnormal and raw returns following TA-based recommendations excluding recommendations that were published during the March 2020 Covid-19 crash. This table shows the returns after buy recommendations have been issued for all asset classes in the sample. Note: ***, **, and * denote significance levels of 0.1%, 1%, and 5%, respectively, for the test statistic.

Panel A: average raw returns (ARR) and average abnormal returns (AAR) in the 5 days following recommendations

Day	Recommendations							
	Stocks		Indices		Commodities		Forex	
	ARR	AAR	ARR	AAR	ARR	AAR	ARR	AAR
1	−0.22%***	−0.39%***	0.15%***	0.12%***	−0.15%*	−0.18%*	0.09%	0.10%
	(−10.45)	(-18.70)	(5.56)	(4.60)	(−2.33)	(−2.43)	(1.51)	(1.71)
2	0.34%***	0.31%***	−0.15%***	−0.18%***	−0.00%	−0.03%	0.07%	0.08%
	(15.81)	(14.96)	(−5.71)	(−6.67)	(−0.03)	(−0.36)	(1.12)	(1.30)
3	0.03%	0.00%	−0.11%***	−0.14%***	0.20%**	0.17%*	0.15%*	0.16%*
	(1.19)	(0.18)	(−4.12)	(−5.08)	(2.96)	(2.33)	(2.40)	(2.61)
4	0.18%***	0.21%***	0.20%***	0.17%***	−0.25%***	−0.27%**	0.04%	0.05%
	(8.51)	(9.96)	(7.36)	(6.40)	(−3.77)	(−3.72)	(0.65)	(0.83)
5	0.17%***	0.16%***	0.13%***	0.11%**	−0.41%***	−0.43%***	−0.06%	−0.05%
	(8.02)	(7.65)	(4.93)	(3.97)	(−6.20)	(−5.91)	(−1.00)	(−0.85)

Panel B: cumulative average raw returns (CARR) and cumulative average abnormal returns (CAAR) in four 5-day intervals following recommendations

Period	Recommendations							
	Stocks		Indices		Commodities		Forex	
	CARR	CAAR	CARR	CAAR	CARR	CAAR	CARR	CAAR
(1, 5)	0.50%***	0.30%***	0.22%***	0.09	−0.62%***	−0.74%***	0.28%	0.34%*
	(10.32)	(6.29)	(3.59)	(1.44)	(−4.19)	(−4.51)	(2.09)	(2.51)
(6, 10)	1.55%***	1.22%***	0.26%***	0.13%*	−0.42%**	−0.54%**	−0.07%	−0.02%
	(32.19)	(26.06)	(4.25)	(2.10)	(−2.82)	(−3.28)	(−0.54)	(−0.17)
(11, 15)	0.62%***	0.01%	−0.09%	−0.22%***	−1.22%***	−1.34%***	0.46%**	0.51%**
	(12.84)	(0.29)	(−1.53)	(−3.67)	(−8.26)	(−8.18)	(3.36)	(3.80)
(16, 20)	−0.15%***	−0.47%***	−0.13%*	−0.26%***	1.72%***	1.60%***	0.07%	0.12%
	(−3.07)	(−10.10)	(−2.12)	(−4.27)	(11.62)	(9.72)	(0.53)	(0.92)

Table 8

Abnormal and raw returns prior to TA-based recommendations excluding recommendations that were published during the March 2020 Covid-19 crash. This table shows the returns before buy recommendations have been issued for all asset classes in the sample. Note: ***, **, and * denote significance levels of 0.1%, 1%, and 5%, respectively, for the test statistic.

Panel A: average raw returns (ARR) and average abnormal returns (AAR) in the 5 days prior to recommendations

Day	Recommendations							
	Stocks		Indices		Commodities		Forex	
	ARR	AAR	ARR	AAR	ARR	AAR	ARR	AAR
−4	0.24%***	0.12%***	−0.14%***	−0.17%***	−1.03%***	−1.05%***	0.14%*	0.15%*
	(11.10)	(5.74)	(−5.34)	(−6.30)	(−15.56)	(−14.34)	(2.26)	(2.47)
−3	0.14%***	0.20%***	−0.06%*	−0.09%**	−0.25%**	−0.27%**	−0.13%*	−0.12%*
	(6.62)	(9.28)	(−2.29)	(−3.25)	(−3.74)	(−3.70)	(−2.20)	(−2.07)
−2	−0.25%***	−0.33%***	−0.10%***	−0.21%***	0.41%***	0.39%***	0.09%	0.10%
	(−11.50)	(−15.85)	(−3.53)	(−4.49)	(6.24)	(5.28)	(1.48)	(1.67)
−1	0.41%***	0.14%***	0.22%***	0.20%***	1.53%***	1.50%***	−0.06%	−0.05%
	(18.90)	(6.85)	(8.25)	(7.29)	(23.08)	(20.44)	(−0.98)	(−0.83)
0	2.12%***	1.44%***	0.30%***	0.28%***	1.56%***	1.54%***	−0.37%***	−0.36%***
	(98.60)	(68.76)	(11.23)	(10.27)	(23.62)	(20.93)	(−6.14)	(−6.08)

Panel B: cumulative average raw returns (CARR) and cumulative average abnormal returns (CAAR) in two 5-day intervals prior to recommendations

Period	Recommendations							
	Stocks		Indices		Commodities		Forex	
	CARR	CAAR	CARR	CAAR	CARR	CAAR	CARR	CAAR
(−9, −5)	−1.53%***	−1.72%***	0.37%***	0.24%***	−1.39%***	−1.51%***	0.74%***	0.79%***
	(−31.89)	(−36.69)	(6.12)	(3.97)	(−9.37)	(−9.18)	(5.46)	(5.94)
(−4, 0)	2.66%***	1.57%***	0.22%***	0.09%	2.23%***	2.10%***	−0.34%*	−0.29%*
	(55.32)	(33.41)	(3.72)	(1.57)	(15.04)	(12.80)	(−2.50)	(−2.16)

7. Conclusion

As analyst recommendations represent publicly available information, according to weak-form market efficiency, investors who follow advice from these analysts should not be able to generate abnormal returns. Existing literature covering the association between technical analysis and profitability focuses mainly on the performance of (single) technical trading rules. Research exploring this relationship through analyst recommendations based on TA is very sparse and most of it is outdated. In addition, current studies only analysed recommendations applied to stocks and indices and were limited to stocks of a single country. Also, no paper has directly compared the performance of TA-recommended equities to their fundamental counterparts. As a consequence, we used event study analysis and calculated risk-adjusted returns in order to identify the determinants and profitability of technical recommendations concerning European stocks, global indices, commodities and forex. The dataset contains recommendations that are published between October 2016 and February 2021. We performed the same analysis for FA-based recommended stocks and compared the abnormal returns surrounding the recommendation date to the abnormal returns of TA-based recommended stocks. Fundamental and technical recommendations are applied to the same set of stocks, so the timing of the recommendations is the only difference.

We find that the abnormal returns of stocks, indices and commodities strongly decline up to the second day before the recommendation day, but then the trend reverses as the abnormal returns are substantial on the recommendation day itself and on the preceding day. As a result, analysts tend to publish recommendations after a short-term uptrend. Particularly the abnormal returns on publication dates are substantial. The fact that TA is based on historical data, the trend-following nature of a large portion of technicians, and the ability of pattern-seekers to identify a short-term dip may explain these findings. With respect to the post-recommendation period, stocks earn positive risk-adjusted returns that persist throughout the following two trading weeks. In contrast, returns tend to decline in the case of indices and commodities. Most average abnormal returns are statistically significant for these asset classes. Recommended forex show an upward trend throughout the full event period. Contrary to the other asset types in the sample, the abnormal forex returns are not as significant in statistical terms. Overall, blindly following recommendations from technical analysts would on average yield positive short-term abnormal returns if it concerns equities and forex, whereas the results are negative in the case of indices and commodities. The results suggest that recommended stocks outperform the other recommended asset classes, while commodities represent the worst-performing asset class. Thus, the forecasting skills of technical analysts differ per asset class. The notion that TA is more effective if non-fundamental factors have a relatively high impact on asset prices (Menkhoff, 2010) indicates that investors may be more subject to behavioural biases and the general market mood when considering stocks.

Next, we find that FA-based recommended stocks move in the opposite direction of technically recommended stocks. Namely, FA-recommended stocks generate significant positive abnormal returns during the pre-recommendation period but yield significantly negative abnormal returns during the post-recommendation period. Therefore, fundamental recommendations outperform technical recommendations before the publication day but clearly underperform in the period following recommendations. The results suggest that TA is a more appropriate investment strategy for short-term investment horizons than FA.

In order to validate the main results, we performed two robustness tests. Firstly, we employed the generalised sign test. Although this non-parametric test led to similar results as its parametric version, it yielded less significant results. This implies that the portion of positive abnormal returns on event days does not differ much from the fraction of positive abnormal returns obtained during the pre-event period (the benchmark). Given that the parametric tests yielded significant results, the high significance levels are determined by the magnitude of abnormal returns during event days and not by the relative number of positive and negative returns. Secondly, we reiterated the main analysis while excluding recommendations that were published during the Covid-19 crash around March 2020. Since the values do not differ much from the original values, the pandemic does not seem to distort the results.

Overall, we conclude that technical analysts exhibit market timing skills and are capable of generating risk-adjusted returns in the case of stocks, which implies that employing TA can be beneficial for investors. Given that we find that technical analysts are able to identify stocks generating returns that are significantly higher than their expected returns, this study contributes to the literature on weak-form market efficiency. Since the technical recommendations in our sample encompass the full definition of TA instead of only strict trading rules, and because we found heterogeneous results with regard to the different asset types, this research provides important new insights regarding the value of TA. Also, the results on the comparison between FA-based and TA-based recommended stocks contribute to the academic literature covering the relative merits of TA and FA.

As a substantial portion of both individual and professional investors employ TA when making investment decisions, the results of this research are highly relevant to practitioners. In particular, the findings suggest that investors need to be cautious when using TA or following TA-based recommendations in the case of indices and commodities. In addition, investors who depend on FA-based recommendations need to be careful as well, since the findings indicate a negative association between FA-based recommended stocks and abnormal returns. Given that the fundamental analysts who publish these recommendations work for large investment banks and brokers, this finding in combination with the potential conflict of interest has implications for regulations as well. More precisely, regulatory entities may need to scrutinise the transparency of fundamental recommendations published by renowned broker-dealers.

This research faces several limitations. One of the main limitations involves the low number of technical recommendations that relate to Forex included in the dataset. We suggest that further research should consider a higher number of technical recommendations involving forex and the other asset classes in the sample, as well as the inclusion of additional asset classes such as cryptocurrencies or exchange-traded funds (e.g. real estate funds). Another drawback of the dataset concerns the fact that TA-based recommendations are published by only two analysts. Further research should include more technical analysts and test whether the results are different when considering different analysts. Investigating the merits of combing technical and fundamental investment strategies based on analyst recommendations is an interesting area for future research. Practically, this demands a replication of the current study but instead employing analyst recommendations that are based on both FA and TA. The pronounced findings on the recommendation day itself suggest that further research may need to investigate the profitability of technical and fundamental analysis considering shorter time intervals (minutes or hours) and the exact time that recommendations have been published. This could have implications for day and swing traders, who use these time intervals in order to place only very short-term trades, and it would provide clearer insights regarding the exact timing of recommendations. Finally, this study focuses only on European stocks. It would be interesting to apply a similar analysis to US stocks or to emerging markets that may be less efficient, such as Asia.

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Appendices

Appendix A. Screenshot of a subset of TA-based recommendations

26-jun-17	**ABN AMRO**	**LONG**	23,22	24,09	**3,75%**	12-jul-17
12-jun-17	**Akzo Nobel**	**LONG**	76,75	77,60	**1,11%**	14-jul-17
4-jul-17	**Volkswagen**	**LONG**	135,80	145,10	**6,85%**	17-jul-17
13-jun-17	**ASML**	**LONG**	116,55	121,65	**4,38%**	18-jul-17
22-mei-17	**ArcelorMittal**	**LONG**	20,39	22,25	**9,12%**	21-jul-17
26-jun-17	**Wessanen**	**LONG**	14,60	13,70	**-6,16%**	25-jul-17
12-jun-17	**SBM Offshore**	**LONG**	13,89	14,61	**5,18%**	3-aug-17
12-jul-17	**ASMI**	**LONG**	52,66	49,27	**-6,44%**	3-aug-17
3-jul-17	**OCI**	**LONG**	19,43	17,90	**-7,87%**	4-aug-17
18-jul-17	**IMCD**	**LONG**	48,17	51,32	**6,54%**	8-aug-17
17-jul-17	**Fagron**	**LONG**	11,32	13,04	**15,19%**	8-aug-17
14-jun-17	**BAM**	**LONG**	4,95	5,08	**2,63%**	10-aug-17
31-jul-17	**RWE**	**LONG**	17,51	20,59	**17,59%**	22-aug-17
2-aug-17	**KBC Groep**	**LONG**	70,19	68,80	**-1,98%**	28-aug-17
16-aug-17	**RELX**	**LONG**	17,84	17,43	**-2,30%**	28-aug-17
24-jul-17	**Galapagos**	**LONG**	69,98	84,01	**20,05%**	13-sep-17
9-aug-17	**Philips**	**LONG**	32,37	34,53	**6,67%**	14-sep-17
10-jul-17	**Bel-20 index**	**LONG**	3836,00	3968,00	**3,44%**	19-sep-17
18-jul-17	**Altice**	**LONG**	20,81	17,53	**-15,76%**	20-sep-17
22-aug-17	**Gemalto**	**LONG**	44,09	39,99	**-9,30%**	22-sep-17
17-aug-17	**DSM**	**LONG**	63,55	67,47	**6,17%**	25-sep-17
7-aug-17	**Royal Dutch Shell**	**LONG**	24,33	25,35	**4,19%**	27-sep-17
12-sep-17	**SBM Offshore**	**LONG**	14,33	15,17	**5,86%**	28-sep-17
18-sep-17	**Bayer**	**LONG**	110,70	115,65	**4,47%**	4-okt-17
25-jul-17	**CAC-40**	**LONG**	5175,00	5349,00	**3,36%**	4-okt-17
25-jul-17	**DAX-Index**	**LONG**	12292,00	12913,00	**5,05%**	4-okt-17
31-jul-17	**Eurostoxx50**	**LONG**	3468,00	3603,00	**3,89%**	17-okt-17
16-okt-17	**Gemalto**	**LONG**	32,53	31,66	**-2,67%**	18-okt-17
11-sep-17	**ASMI**	**LONG**	50,87	55,48	**9,06%**	19-okt-17
2-okt-17	**Proximus**	**LONG**	29,17	28,48	**-2,37%**	23-okt-17
15-aug-17	**Corbion**	**LONG**	25,20	27,79	**10,28%**	24-okt-17
3-okt-17	**Bund Future**	**LONG**	161,22	162,67	**0,90%**	1-nov-17
9-okt-17	**Nestlé**	**LONG**	72,58	73,00	**0,58%**	7-nov-17

Appendix B. Screenshot of a subset of FA-based recommendations

ASML

23 actieve adviezen | Sentiment:

Overzicht | Adviezen

Adviezen

Datum	Guru	Adviezen	Koersdoel	
8 jan 21	DZ Bank	Kopen	€ 460,00	13,89%
7 jan 21	UBS	Houden	€ 395,00	0,00%
5 jan 21	Liberum Capital	Kopen	€ 460,00	13,23%
5 jan 21	RBC Capital Markets	Kopen	€ 540,00	32,92%
4 jan 21	Sanford C. Bernstein & Co	Houden	€ 325,00	0,00%
4 jan 21	Citigroup Smith Barney	Kopen	€ 460,00	15,71%
18 dec 20	Bank of America Merrill Lynch	Kopen	€ 439,00	13,94%
17 dec 20	Goldman Sachs	Kopen	€ 443,00	14,98%
10 dec 20	UBS	Houden	€ 350,00	0,00%
10 dec 20	Morgan Stanley	Kopen	€ 420,00	9,57%
7 dec 20	Stifel Nicolaus	Kopen	€ 420,00	12,56%
1 dec 20	Barclays Capital	Kopen	€ 425,00	16,81%
30 nov 20	Sanford C. Bernstein & Co	Houden	€ 325,00	0,00%
27 nov 20	Goldman Sachs	Kopen	€ 395,00	7,82%
27 nov 20	Sanford C. Bernstein & Co	Houden	€ 292,00	0,00%

Summary

Introduction

Classic finance theory states that predicting the future price movements of stocks is a complex task. Yet, many stock market analysts issue recommendations about the future trends of various securities. As a result, academic research has covered the implications of these analyst recommendations thoroughly. However, this literature consists almost solely of recommendations that are based on fundamental analysis, while its technical counterpart remains relatively uncharted in this regard (Gerritsen, 2016). Some of these analysts and traders claim they can beat the market by means of technical analysis (TA), which has become a popular strategy (Zaloom, 2003). If this is the case, it would imply that the Efficient Market Hypothesis (Fama, 1970), which states that all available information is already incorporated in stock prices, does not hold. Since analyst recommendations are publicly available, investors should not be able to profit from them.

TA is one of the two main approaches used by investors and traders to forecast price developments of securities. Investors, traders and analysts who employ TA are also called “chartists” or “technicians”. TA is based on historical stock prices and trading volume and finds its roots in the Dow Theory (Murphy, 1999). The alternative commonly used approach to predict price trends is fundamental analysis, which focuses on estimating intrinsic values of securities based on economic factors. As a result of the Covid-19 crisis and the opportunities that came with it due to increasingly volatile financial markets and the stimulus packages from governments, many retail investors have opened trading accounts (Ortmann et al., (2020). Additionally, a broad range of TA indicators and tools are easily accessible nowadays. Menkhoff (2010) found that 87% of fund managers view TA at least as a relatively important source of information and that it dominates fundamental analysis when making investment decisions with a forecast horizon up to a few weeks. According to Taylor and Allen (1992), 90% of foreign exchange market dealers rely on both FA and TA. Moreover, according to Menkhoff (2010), TA is the most frequently used trading strategy in the foreign exchange and commodity futures markets. With regard to non-professional investors, Hoffmann and Shefrin (2014) stated that TA is more popular than fundamental analysis among individual investors. Therefore, understanding the consequences of using TA is highly important since it impacts a large portion of both professional and retail investors.

Common tools of TA concern technical indicators, stop loss, stop gain and RSI filters (Teixeira & Inacio de Oliveira, 2010). Although traders commonly use these TA tools in practice, academic research that covers the effectiveness of TA is relatively lacking (Alanazi & Alanazi, 2020). Most papers aimed to address this research gap by testing whether investment strategies based on technical trading rules yield abnormal returns in particular markets and time periods. Research on strict trading rules only emphasised the efficacy of TA-based trading rules, which represents only a portion of TA techniques (Roscoe & Howorth, 2009). As a result, this stream of research only provides implications about the potential of TA ex-post and not about the observed performance of investors who employ TA strategies.

In response to the academic criticism they face, many TA users claim that TA involves much more than simply following trading rules and that it relates more to art than science (Gerritsen, 2016). In order to take into account the broader perspective of TA instead of only TA-based trading signals, focusing on the recommendations that are published by technical analysts may provide more insights. However, research covering the profitability of buy or sell recommendations issued by (professional) technical analysts is limited. The fact that research covering the association between technical recommendations and stock returns is minimal, combined with the notion that many investors consider TA when making investment decisions, demands further investigation with regard to this relationship. Therefore, the problem statement we aim to examine is whether analyst recommendations that are solely based on technical analysis are associated with abnormal future returns.

The fact that research covering the association between technical recommendations and stock returns is minimal, combined with the notion that many investors consider TA when making investment decisions, demands further investigation with regard to this relationship. Therefore, the problem statement we aim to examine is whether analyst recommendations that are solely based on technical analysis are associated with abnormal future returns. Although TA is most popular among investors who focus on commodities and forex markets (Menkhoff, 2010), no evidence exists on the relationship between technically recommended commodities and forex, and their returns. As a result, we aim to investigate whether technical analysis works better for stocks, forex, indices or commodities. Given that many chartists are trend-seekers, who pursue to identify stocks based on their momentum (Roscoe & Howorth, 2009), we explore whether buy recommendations follow positive abnormal returns. Finally. no paper has directly compared the performance of TA-recommended stocks to their fundamental counterparts. This leads to the question whether technical analysts have superior or inferior predictive skills regarding stock prices compared to fundamental analysts. In order to answer the problem statement and accompanying research questions, we employ event study analysis based on recommendations that have been issued between 2016 and 2021.

Relative to existing research, this study contributes to academic literature as it involves more recent data, differentiates between various types of investment vehicles, considers equities from multiple countries, and because it provides a comparison between the abnormal returns of TA and FA recommended stocks. Since existing literature mainly emphasised the profitability of technical trading rules (in isolation), this paper contributes to the level of understanding regarding the determinants and profitability as it circumvents data snooping issues and encompasses the full definition of TA. Namely, technical analysts may base their recommendations also on a visual analysis of the data as well as “gut feeling”, which cannot be measured with technical trading rules. Additionally, the results of this thesis would have implications for the ongoing debate regarding the validation of the Efficient Market Hypothesis, as this paper tests whether the market is weak-form efficient. As the effect of TA on investor performance impacts a large number of investors, this topic is relevant to both individual and professional investors, regardless of whether they currently employ TA or not, as well as to brokers, academics and market supervisors.

Literature Review and Hypotheses

Many traders and investors use technical analysis as an investment strategy (Menkhoff, 2010). Although many traders employ TA as a means to analyse all types of financial assets, it is the most frequently used investment strategy in the foreign exchange and commodity markets. Its popularity is partly explained by the fact that TA tools are widely available and easily accessible. Another reason is related to its simplicity since even traders without a finance background can rely on standardised trading rules that indicate when one should buy or sell an asset. TA is mainly based on data that stem from historical prices or trading volume (Park & Irwin, 2007). Pring (2002, p. 2), an influential technical analyst, provides a more concrete definition: "The technical approach to investment is essentially a reflection of the idea that prices move in trends that are determined by the changing attitudes of investors toward a variety of economic, monetary, political, and psychological forces. The art of technical analysis, for it is an art, is to identify a trend reversal at a relatively early stage and ride on that trend until the weight of the evidence shows or proves that the trend has reversed." Pertaining to this definition, some academics and practitioners view TA as a self-fulfilling prophecy (Menkhoff, 1997). The most common TA tools and indicators are trading range breakout (TRB), moving averages, Bollinger bands, relative strength index (RSI), moving average convergence divergence (MACD), and on-balance volume (Gerritsen, 2016).

In case certain methods that are based on TA allow traders to consistently outperform the market, a buy-and-hold strategy or generate abnormal (risk-adjusted) returns, the Efficient Market Hypothesis (Fama, 1970) does not hold. More precisely, such outperformance would contradict the weak form of the Efficient Market Hypothesis. Weak-form market efficiency articulates that all information concerning past trading data is already incorporated in current prices. Related to the Efficient Market Hypothesis, the random walk hypothesis (Fama, 1965) states that future movements of stock or market prices cannot be predicted based on their past movements or trends as all new information is directly absorbed by the market and thus reflected in the prices. Therefore, only unanticipated news or events can lead to price changes, independent of past prices or trading volume. In this regard, extrapolating past changes in prices to future price changes using TA should have no value for traders or investors. Nevertheless, since the 1960s extensive research has been conducted on the profitability of TA (Park & Irwin, 2007).

Existing research aims to identify the value of investments in four ways. The largest portion of this research covered the merits of technical trading rules. Another approach focused on the intersection between TA, stock returns and individual investor behaviour. The remaining two categories assessed the value of TA on the basis of the combined value of fundamental and technical analysis and based on technical analyst recommendations.

Most of the academic literature that covers TA focuses on the profitability of TA-based trading rules. Park and Irwin (2007) have comprehensively reviewed the papers that cover TA and categorised this literature into two groups, namely early studies (1960-1987) and modern studies (1988-2004). In general, the early studies failed to find evidence of the profitability of technical trading rules in the stock market, whereas many studies covering foreign exchange and futures markets were able to find significant net profits. Notwithstanding, these early studies face substantial limitations. For instance, they did not consider trading rule optimisation, data snooping issues, and they only tested one or two trading rules. With regard to the modern studies, 20 studies found negative results concerning TA-based signals, 56 studies obtained positive findings and 19 studies arrived at mixed results. Particularly, modern studies found that technical trading rules yielded significant economic returns in the stock, forex and futures markets only until the early 1990s.

Although the modern studies improved upon the limitations of the early studies by taking into account the risk of trading rules, testing more trading rules, employing parameter optimisation and using more sophisticated bootstrap methods, most of them still contained data snooping biases. Data snooping biases arise due to the fact that researchers will eventually find that technical trading rules yield returns that are higher than the market return or the buy-and-hold strategy if they try enough rules with enough variables (Jensen, 1967).

Shynkevich (2011) adjusted for data snooping and examined whether technical trading rules yield superior predictive accuracy when applied to small-cap sector and technology industry portfolios between 1995 and 2010. Similar to the results of Park and Irwin (2007), the findings of Shynkevich (2011) pose that TA-based signals are able to outperform the buy-and-hold strategy for both small-cap and technology portfolios in the first half of the sample period (1995-2002), but fail to detect statistically significant returns in the second half of the portfolio (2003-2010). Bajgrowicz and Scaillet (2012) used the false discovery rate in order to adjust for data snooping bias and applied this method to daily prices of the Dow Jones Industrial Average index from 1897 to 2011. They came to similar conclusions as the trading rules in their sample did not outperform the market index. Thus, based on the results of Park and Irwin (2007), Shynkevich (2011) and Bajgrowicz and Scaillet (2012), the performance of TA has declined over time. This suggests that the underlying aspects of the equity market have become more efficient during the past two decades.

More recent papers use sophisticated technology to account for data snooping biases and other limitations faced by earlier studies. Teixeira and Inacio de Oliveira (2010) examined whether an intelligent trading system based on TA techniques, in particular on data derived from asset prices and trade volume, is able to generate statistically significant profits. They found that their method yielded better results in comparison to a buy-and-hold strategy. Amongst other recent literature, Sezer et al. (2017) employed a deep neural-network-based trading system that optimises TA parameters and also arrived at the conclusion that their algorithms outperform the buy-and-hold strategy in terms of stock trading performance.

In contrast to studies that examined trading rules, we aim to circumvent data snooping bias by conducting event study analysis on analyst recommendations. Another advantage of employing analyst recommendations concerns the fact that technical trading rules may not cover the full spectrum of TA. According to Roscoe and Howorth (2009), chartists consist of two groups, namely trend-seekers (or “momentum” traders) and pattern-seekers. Trend-seekers try to identify stocks that are headed in a certain direction, whereas pattern-seekers aim to predict trend-reversals and price movements of stocks or other assets. As a consequence, next to quantitative techniques, TA also involves the recognition of certain patterns in the data by means of visually inspecting a time-series plot (Menkhoff and Taylor, 2007). In contrast to pure technical trading rules, technical analysts are likely to consider the visual and “gut feeling” aspects as well.

According to Menkhoff (2010), TA is more likely to be effective if security prices are influenced by non-fundamental factors that can be driven by general market mood and investors’ behavioural biases such as overconfidence or fear, which could eventually lead to stock market bubbles and their subsequent crashes. However, there is a striking absence of evidence on the exact strategies and behaviour of individual TA investors (Roscoe & Howorth, 2009). An important paper in this respect is the one from Barber and Odean (2002), who found that individual investors overtrade and that this has a detrimental effect on their performance. The authors argue that overtrading is the result of overconfidence. An interesting hypothesis would be that this underperformance found by Barber and Odean (2002) is explained by the fact that a relatively large number of individual investors employ TA. Related to this, Hoffmann and Shefrin (2014) illustrated that optimistic and overconfident investors seem to be more likely to use TA instead of fundamental analysis or an alternative strategy.

In contrast to the papers that solely cover the predictive abilities of technical trading rules, Lewellen, Lease and Schlarbaum (1980) and Hoffmann and Shefrin (2014) took into account the behavioural aspect of TA by covering the linkage between TA and individual investors. Particularly, Hoffmann and Shefrin (2014) used data from the period 2000-2006 and compare the returns of traders who use TA to the returns of traders who use fundamental analysis. Their main findings indicate that investors who use technical indicators earn lower returns, are more likely to speculate, trade more frequently, hold more concentrated portfolios and have a higher exposure to non-systematic risk. As a result, technicians are likely to incur relatively high transaction costs.

As a substantial portion of research has provided evidence to the detriment of TA, some technical analysts responded to the criticism by claiming that the eminence of TA may not lie in stringently implementing technical trading rules, but rather in synthesising multiple signals into one recommendation (e.g. Dawson, 1985; Gerritsen, 2016), as well as considering the visual aspect of TA and gut feeling (Roscoe & Howorth, 2009). Cowles (1933) found that recommendations from technical analysts that were published in the Wall Street Journal underperformed the buy-and-hold strategy. Brown, Goetzmann and Kumar (1998) used the same dataset as Cowles (1933), but they employed different statistical methods and concluded that the Wall Street Journal recommendations yielded risk-adjusted abnormal returns. Dawson (1985) examined whether TA-based investment recommendations by a Singapore investment advisory firm would help investors to earn excess returns, but his results suggest that the recommended shares traded on the Singapore Stock Exchange did not outperform the market. Gerritsen (2016) also investigated the value of TA from this angle. In fact, he examined whether these TA-based recommendations lead to future abnormal returns and concluded that this is not the case. His findings are only based on Dutch stocks and the main Dutch index, namely the AEX. He also found that the recommendations used by the technical analysts follow standard technical trading rules, which implies that TA does not seem to add value for investors.

A substantial portion of investors and traders use both fundamental and technical analysis (Taylor & Allen, 1992). In contrast to technical analysts, fundamental analysts aim to determine the intrinsic value of an investment instrument, which is derived from the performance of the particular company and the economy in general (Lam, 2004). Many brokers and broker-dealers issue stock recommendations that are based on fundamental analysis conducted by analysts from their research department. Commonly, these analysts assign "buy'', "hold" or "sell" ratings to particular stocks. Recent research regarding the veracity of fundamental recommendations suggests that analysts fail to outperform the market on a consistent basis (e.g. Barber et al., 2001, 2003). Moreover, Baker and Dumont (2014) concluded that stocks with "buy" ratings consistently underperform equities with "hold" ratings. The authors argue that this finding could imply that analysts may have the intention to mislead investors. These findings suggest that analysts who use fundamental information simply fail to accurately predict the intrinsic value of stocks, or that the incentives of broker-analysts are not in alignment with the interests of investors who use the analyst reports. With regard to the latter, principal-agency problems may lead brokerage firms to recommend stocks that benefit them but not investors who rely on reports that are supposedly objective. In contrast to the studies that find a negative association between buy-recommendations based on fundamental analysis and abnormal returns, Gerritsen and Lötter (2015) showed that recommended stocks with the highest ratings are associated with significant and positive abnormal returns in the short term.

Since existing research that focuses on the relationship between TA-based recommendations and returns is sparse, this paper aims to contribute to the current literature by evaluating the (abnormal) returns surrounding technical recommendations by means of event study analysis using recent data and equities that are listed in different countries, and by comparing the results for various asset types. The forecasting abilities of technical analysts can be measured in both absolute and relive terms. The former relates to market timing, while the latter involves identifying equities that outperform the market in a certain time period (Gerritsen, 2016). In the event that technical analysts have particular market timing skills, following buy recommendations should lead to positive raw returns. In case technicians are able to outperform by means of obtaining risk-adjusted returns, recommendations should be followed by positive abnormal returns. Since the performance of TA-based recommended assets could relate to either absolute or relative price patterns, the analyses include both raw and abnormal returns. However, the main focus of this paper concerns abnormal returns as this analysis takes risk factors into account and thus provides more meaningful insights.

Given weak-form market efficiency (Fama, 1965), the fact that Cowles (1933), Dawson (1985) and Gerritsen (2016) failed to identify a positive association between TA recommendations and returns, that some papers found that the profitability of TA has diminished over time (e.g. Shynkevich, 2011), and because many papers found that technical trading rules do not yield abnormal returns after adjusting for data snooping, we expect that employing TA-based recommendations does not lead to abnormal returns. Following the notion that investors predominantly use TA for short-term investment horizons (Menkhoff, 2010), the main hypothesis of this paper is:

H1: Following technical analyst recommendations is not related to statistically significant abnormal returns shortly after the recommendation.

The second analysis concerns the returns preceding recommendations. As TA solely uses past data, by definition it builds on past price patterns. Only Bollinger bands and the Relative Strength Index are countertrend indicators (Park & Irwin, 2007). As a result, all other TA tools should follow the (short-term) trend and thus generate a buy signal if equities are in an upward trend. In addition, one of the main groups of technicians, in particular trend-seekers or “momentum” traders, select assets on the basis of their direction. In addition, Gerritsen (2016) found that upward and downward trends triggered buy and sell recommendations, respectively. As a consequence, we expect buy recommendations to follow a period of positive price patterns, resulting in positive abnormal returns during the pre-recommendation period. This leads to the second hypothesis:

H2: Buy recommendations follow a period of positive abnormal returns

No study has compared the profitability of these asset types using recommendations from technical analysts. However, according to Taylor (1992), a substantial portion of forex traders employ technical analysis. In addition, since some papers that examined the profitability of technical trading rules, including recent ones, such as Alanazi and Alanazi (2020), found that TA is more effective for forex compared to stocks, indices and commodities, the third hypothesis is:

H3: TA recommendations for forex lead to higher abnormal returns after the recommendation relative to stocks, indices and commodities.

Although some research exists concerning the predictive capabilities of technical and fundamental analyst recommendations in isolation, no consensus has been reached yet regarding their profitability with reference to each other. Current literature has not directly investigated the relative performance of TA-based recommendations and FA-based recommendations. In addition, since Hoffmann and Shefrin (2014) found that individual investors who use TA obtain lower returns than those who use fundamental analysis, the fourth hypothesis is:

H4: Abnormal returns following technical recommendations are higher than abnormal returns following fundamental recommendations.

Research Design

In terms of data retrieval, this research requires investment recommendations from technical analysts. BTAC Visual Analysis provided these data. The dataset consists of TA recommendations for stocks, major indices, forex and commodities for various countries and it covers the period between October 2016 and February 2021. Attached to their recommendations, they included notes about the rationale behind buy, sell or hold recommendations. Based on these notes, the technical analysts who provided the data considered technical trading rules as well as visual interpretations of price movements and trends. As a result, the TA-based recommendations in our sample comply with the exhaustive definition of TA. In order to test the hypotheses, we collected the risk-free rate, the prices of the recommended European stocks, global indices, forex, and commodities in our dataset during the given period, as well as daily returns including reinvested dividends.

Current research examining the performance of TA benchmarks the returns of employing this strategy either to market returns, buy-and-hold returns or expected returns. We focus on the latter in order to take the amount of risk into account. Given that we aim to determine the determinants and profitability of TA, all hypotheses require the computation of abnormal returns in the 30-day period around the dates of the technical analyst recommendations in order to conduct event study analysis. Particularly, (-9,0) will be treated as the pre-recommendation period and (1,20) is will serve as the post-recommendation period. With regard to stocks, the first step is to assemble daily returns, including reinvested dividends, for each security in the sample. The next step involves the calculation of abnormal return for all securities, which is the difference between the realised excess return and the expected excess return for stock *i* on day *t* (equation 1). As a result, these components need to be calculated first. The realised excess return is the difference between the raw stock return (including reinvested dividends) and the risk-free interest rate (equation 2), whereas the expected excess return is estimated based on the Fama-French-Carhart 4-factor model (equation 3). In alignment with current research covering the profitability of TA, we use the Fama-French-Carhart 4-factor model in order to adjust for the risk level. Concerning recommendations on indices, commodities and forex, the process of calculating abnormal returns is identical to the one for stocks, except for the computation of expected returns. Particularly, for these asset classes, the expected return is equal to the mean-adjusted excess return, using the period of 250 days preceding the pre-recommendation period (equation 4). The next step concerns estimating the average abnormal returns (AAR) for each trading day in the pre-recommendation period and the post-recommendation period by taking the average of the abnormal returns for each event day (equation 5). Then, we employ a t-test in order to determine whether the calculated average abnormal returns are significantly different from zero (equation 6). Afterwards, we calculate the cumulative average abnormal returns (CAAR) for various 5-day event windows by taking the sum of the AARs for each event window (equation 7) and test whether these cumulative values are significantly different from zero by means of a t-test (equation 8). With respect to fundamental recommendations, the procedure is identical to technical recommendations. In alignment with Metghalchi et al. (2008), we perform an Independent Samples t-Test (equation 9) in order to compare the average abnormal returns surrounding both types of recommendations.

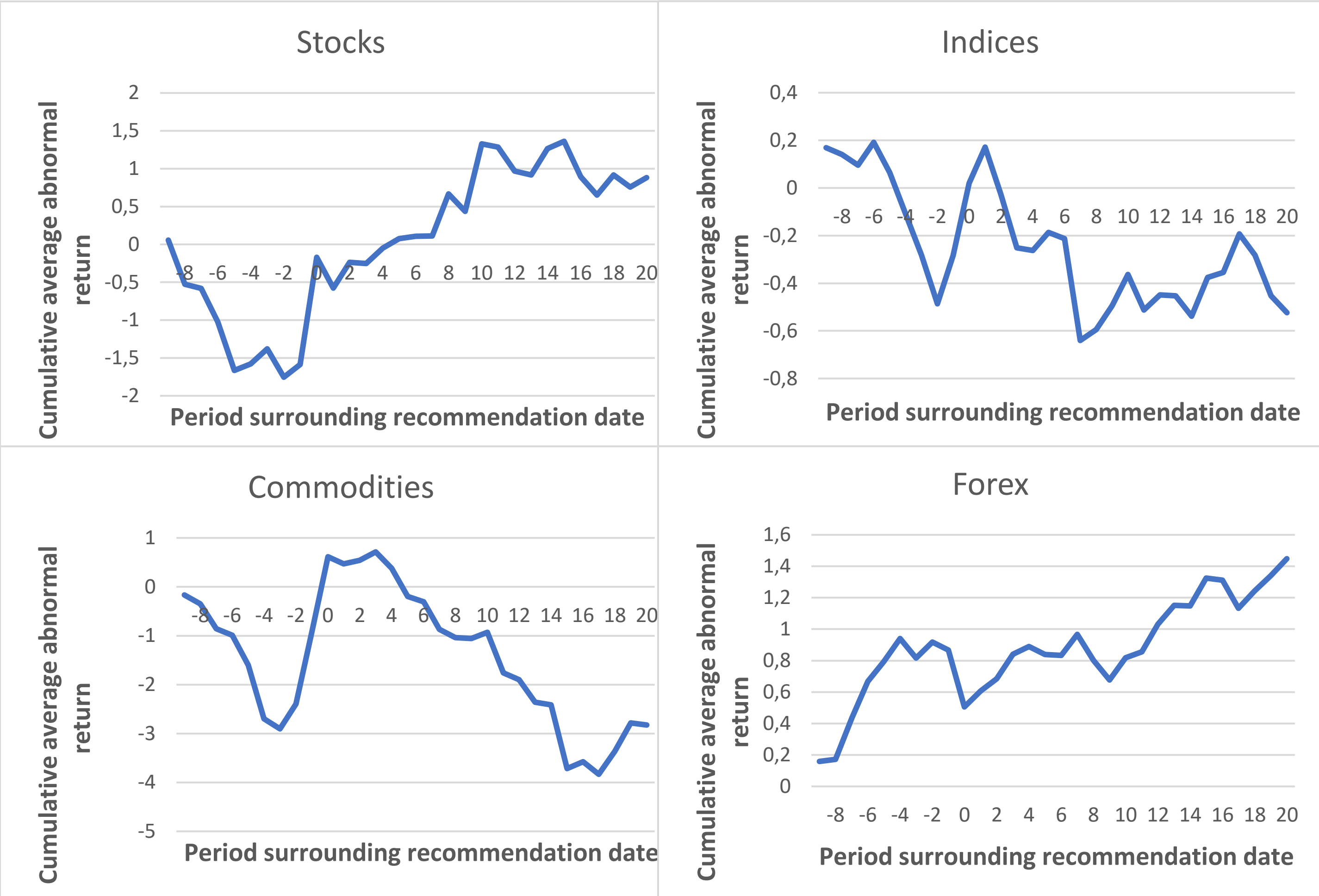
Data Analysis and Results

Concerning the pre-recommendation period, the CARRs and CAARs of stocks, commodities and forex are both economically and statistically significant in the (-9, -5) period, but vary in terms of their signs.

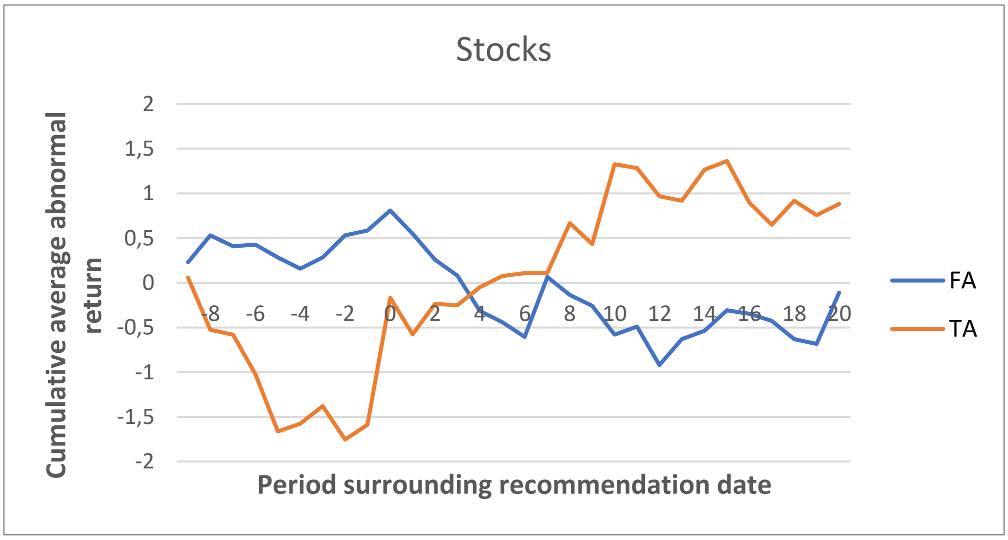
Specifically, stocks and commodities show a negative sign in this period (-1.66% and -1.60%, respectively), whereas the results are positive for forex (0.79%) and the CAAR is insignificantly positive for indices. However, the the trend reverses right before publications as the abnormal returns are substantial on the recommendation day itself and on the preceding day. On the publication day, the AARs of stocks, indices and commodities are 1.42%, 0.30% and 1.53%, respectively. Overall, the results suggest that TA-based recommendations on stocks, indices and commodities follow positive and sizable abnormal returns, particularly on event days 0 and -1. This matches the notion that most TA-based strategies are trend-following. The fact that TA is based on historical data and the trend-following nature of a large portion of technicians may explain these findings. Given that the abnormal returns of stocks, indices and commodities strongly decline up to the second day before the recommendation day and significantly rise right before recommendations implies that pattern-seekers are able to identify a short-term bottom.

With respect to the post-recommendation period, stocks earn positive risk-adjusted returns that persist throughout the following two trading weeks. In contrast, returns tend to decline in the case of indices and commodities. Most average abnormal returns are statistically significant for these asset classes. Recommended forex show an upward trend throughout the full event period. Contrary to the other asset types in the sample, the abnormal forex returns are not as significant in statistical terms. Corresponding to the full post-recommendation period (1, 20), the CAARs of TA-based recommended stocks, indices, commodities and forex are 1.05%, -0.54%, -3.44% and 0.94%, respectively. Their respective t-statistics are 11.80, -9.12, -10.48 and 3.53, which implies that these values are statistically significant. Thus, adhering to TA-based recommendations and holding the asset throughout the full post-recommendation period yields positive abnormal returns in the case of stocks and forex, whereas this strategy earns negative returns if the recommendations concern indices and commodities. Overall, blindly following recommendations from technical analysts would on average yield positive short-term abnormal returns if it concerns equities and forex, whereas the results are negative in the case of indices and commodities. The results suggest that recommended stocks outperform the other recommended asset classes, while commodities represent the worst-performing asset class. Thus, the forecasting skills of technical analysts differ per asset class. The following figure summarises these results.

Given that fundamental analysis is the main counterpart of technical analysis when considering investment strategies, we compare the returns following and preceding technical recommendations to returns surrounding fundamental recommendations. The FA-based recommended stocks are identical to the TA-based recommended stocks. Therefore, the only difference concerns the timing of recommendations, which minimises unobserved heterogeneity. This allows us to directly compare the performance of technical and fundamental analysts. As the abnormal returns tend to be significantly higher than zero during the two trading weeks before the event day, FA-based recommendations seem to follow the medium-term trend. Also, the results suggest that following fundamentally based recommendations has an adverse effect on returns during the first few days but a reversal takes place during the second trading week, which lasts at least up to



the fourth trading week. Therefore, we find that FA-based recommended stocks move in the opposite direction of technically recommended stocks. Namely, FA-recommended stocks generate significant positive abnormal returns during the pre-recommendation period but yield significantly negative abnormal returns during the post-recommendation period. As a consequence, fundamental recommendations outperform technical recommendations before the publication day but clearly underperform in the period following recommendations. The results suggest that TA is a more appropriate investment strategy for short-term investment horizons than FA. The fact that TA is generally used for short term investment horizons and FA for the long term could explain these findings. The following figure illustrates these outcomes graphically.



In order to validate the main results, we performed two robustness tests. Firstly, we employed the generalised sign test. The GST is a nonparametric checks whether the number of positive abnormal returns on each day and week in the event period differs significantly from the number of positive abnormal returns in the period prior to the pre-recommendation period (-260, -10). Although this non-parametric test led to similar results as its parametric version, it yielded less significant results. This implies that the portion of positive abnormal returns on event days does not differ much from the fraction of positive abnormal returns obtained during the pre-event period (the benchmark). Given that the parametric tests yielded significant results, the high significance levels are determined by the magnitude of abnormal returns during event days and not by the relative number of positive and negative returns. Secondly, we reiterated the main analysis while excluding recommendations that were published during the Covid-19 crash around March 2020. Since the values do not differ much from the original values, the pandemic does not seem to distort the results.

Discussion

Given that the technical analysts who provided the recommendations in the sample employed both technical trading rules and visual analysis, the findings indicate that TA is appropriate for analysing stocks and proves unsuitable for indices and commodities. The implications for forex are uncertain as the abnormal returns obtained in the recommendation period are relatively insignificant. The notion that TA is more powerful when applied to assets that are subject to non-fundamental factors such as behavioural biases (Menkhoff, 2010) may explain the outcomes of our analysis. Specifically, the outperformance of technically recommended stocks relative to their peers implies that investors are more prone to these non-fundamental factors when considering equities.

With regard to the pre-recommendation period abnormal returns of TA-based recommended stocks, indices, commodities and FA-based recommended stocks are positive and both economically and statistically significant regarding the trading week before the publication day of recommendations. The abnormal returns on the recommendation day itself are particularly high. Given that almost all technical trading rules, signals and indicators are based on historical data implies they are designed to follow the trend, while only a few TA tools lead to counter-trades. This may explain why TA-based recommendations tend to follow short-term abnormal returns. Additionally, the fact that abnormal returns of stocks, indices and commodities strongly decline up to the second day before the recommendation day and significantly rise right before recommendations implies that pattern-seekers are able to identify a short-term bottom.

However, the observation that abnormal returns of FA-based recommended stocks are positive before the recommendation and negative after the recommendation has different determinants relative to technical recommendations. In fact, FA-based recommendations are issued too late. As introduced in subsection 2.4, information asymmetry and conflict of interest could explain these results. In contrast to the technical analysts that issued the recommendations contained in the dataset, the fundamental analysts work for large investment banks and brokers. As a result, broker-dealers, where these fundamental analysts work, may have already reacted to the advice before it is made available to the public. This may relate to the potential inside information these firms have, which allows them to act on this information before they publish recommendations that are available to the general public. A conflict of interest exists involving investment banks and (un)sophisticated investors who use analyst recommendations to base their investment decisions on. Firstly, investment banks have an incentive to issue unrealistically positive recommendations in order to avoid losing clients or foregoing the possibility to attract new clients in the future. Secondly, there is a positive correlation between the number of transactions and revenues. If brokers issue “hold” ratings, investors are less likely to make transactions than if brokers issue “buy” ratings. Accordingly, it is not surprising that the buy-sell ratio of the total recommendations in the dataset is eminent, even if the number of hold ratings is added to the number of sell ratings. Due to these reasons, the intrinsic value of a stock may be consistently lower than the value stated in a recommendation, leading to low or negative abnormal returns in the period after the recommendations.

Conclusion

Overall, we conclude that technical analysts exhibit market timing skills and are capable of generating risk-adjusted returns in the case of stocks, which implies that employing TA can be beneficial for investors. Given that we find that technical analysts are able to identify stocks generating returns that are significantly higher than their expected returns, this study contributes to the literature on weak-form market efficiency. Since the technical recommendations in our sample encompass the full definition of TA instead of only strict trading rules, and because we found heterogeneous results with regard to the different asset types, this research provides important new insights regarding the value of TA. Also, the results on the comparison between FA-based and TA-based recommended stocks contribute to the academic literature covering the relative merits of TA and FA.

As a substantial portion of both individual and professional investors employ TA when making investment decisions, the results of this research are highly relevant to practitioners. In particular, the findings suggest that investors need to be cautious when using TA or following TA-based recommendations in the case of indices and commodities. In addition, investors who depend on FA-based recommendations need to be careful as well, since the findings indicate a negative association between FA-based recommended stocks and abnormal returns. Given that the fundamental analysts who publish these recommendations work for large investment banks and brokers, this finding in combination with the potential conflict of interest has implications for regulations as well. More precisely, regulatory entities may need to scrutinise the transparency of fundamental recommendations published by renowned broker-dealers.

This research faces several limitations. One of the main limitations involves the low number of technical recommendations that relate to forex included in the dataset. We suggest that further research should consider a higher number of technical recommendations involving forex and the other asset classes in the sample, as well as the inclusion of additional asset classes such as cryptocurrencies or exchange-traded funds (e.g. real estate funds). Another drawback of the dataset concerns the fact that TA-based recommendations are published by only two analysts. Further research should include more technical analysts and test whether the results are different when considering different analysts. Investigating the merits of combing technical and fundamental investment strategies based on analyst recommendations is an interesting area for future research. Practically, this demands a replication of the current study but instead employing analyst recommendations that are based on both FA and TA. The pronounced findings on the recommendation day itself suggest that further research may need to investigate the profitability of technical and fundamental analysis considering shorter time intervals (minutes or hours) and the exact time that recommendations have been published. This could have implications for day and swing traders, who use these time intervals in order to place only very short-term trades, and it would provide clearer insights regarding the exact timing of recommendations. Finally, this study focuses only on European stocks. It would be interesting to apply a similar analysis to US stocks or to emerging markets that may be less efficient.