Do analysists' consensus recommendations have an investment value? A study conducted on the 20 stocks included in the BEL20 index

Auteur : Kever, Mats
Promoteur(s) : Hubner, Georges
Faculté : HEC-Ecole de gestion de l'Université de Liège
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DO ANALYSTS' CONSENSUS RECOMMENDATIONS HAVE INVESTMENT VALUE: A STUDY CONDUCTED ON THE 20 STOCKS INCLUDED IN THE BEL20 INDEX

Jury:
Promoter:
Georges HÜBNER
Reader(s):
Marie LAMBERT
Vincent COLOT

Dissertation by
Mats KEVER
For a Master in Business Engineering,
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Preface and Acknowledgements

This Master Thesis was written between September and December 2020 as part of the Master's program in Financial Engineering at HEC-Liège. The research focusses on the analysis of the investment value that lays within the consensus of analyst recommendations with special attention to the 20 stocks included in the BEL20 Index.

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1 Introduction

This first chapter's purpose is to introduce the reader to the subject of analyst recommendations, the consensus of those and the value behind them. To start off, today's knowledge about the topic is briefly discussed to bring the reader up to date on the discoveries that have been made in the past. Later on, the research objective of this master thesis is presented and quickly explained.

1.1 Context and Current Situation

Year after year brokerage firms spend large sums on analysts' research but the information role of security analysts and their recommendations have been the subject of many discussions. Stock analysts create new information by processing public information; they convey negative information through the release of a negative recommendation (e.g., Sell or Strong Sell) or a downgrade to a lower recommendation. Analogously, they convey positive information through the issuance of a positive recommendation (e.g., Buy or Strong Buy) or an upgrade to a more favorable recommendation. Analysts serve as an important agent between investors and publicly traded companies and release earnings forecasts and stock recommendation reports.

However, Fama (1970) suggests that in an efficient market, stock prices reflect all available information at any point. As a result of this so-called *Strong Market Hypothesis*, investors should not be able to generate excess returns by following analysts' recommendations. On the other hand, information is rarely perfect, and the markets are not efficient, which justifies the existence of analysts with a superior ability to convey information to market participants. Hence, if stock prices would reflect all available information, the demand for analyst recommendations would be non-existent and brokerage firms would not spend large amounts to compensate their services. According to Grossman and Stiglitz (1980), the market is not perfectly efficient and prices do not reflect all available information which stems the need of analysts to serve investors as a market agent. The role of these market agents is to find undervalued and overvalued securities to keep the markets efficient.

Due to these contrarian thoughts on efficient markets, the value behind these recommendations has been the subject of much research reports in recent history. One of the first papers published on this very matter was released in 1933 by Cowles and investigates the forecasting abilities of stock market forecasters. Since then, many questions and aspects related to analyst recommendations have been investigated, such as the price reaction time to new recommendations, post-recommendation drifts, the difference of the investment value between new recommendations, revisions and reiterations, different strategies related to recommendations, factors that influence recommendations and many more. The different discoveries of the existing literature are discussed under section 2 of this paper.

1.2 Research objective

The aim of this master thesis is to investigate the investment value that lies within the consensus of analyst recommendations. Previous studies have repeatedly examined the influence recommendations have on the return of U.S. stocks, however, very few have analyzed the impact on other markets. To add to the existing literature, this research will inspect the impact of the analysts' consensus recommendation on the 20 stocks of the major Belgian stock market index (BEL20).

The main research objective of this paper is to answer the question if analysts' consensus recommendations, made on the stocks figuring in the Belgian stock index BEL20, present value for investors and if it is possible to build profitable investment strategies on the basis of these recommendations.

Further explanation on how this question is investigated can be found under section three, *Research Methodology*.

1.3 Overview

The remainder of this paper is as follows.
In section 2, the existing literature is reviewed and summarized. This will put the reader on a level playing field giving him/her an overview of the latest developments and findings about this very subject. To my understanding and in my opinion, the selected topics and papers present the most interesting and important discoveries around the impact of analyst recommendations.
Section 3 introduces the research part of this study. First, the most important concepts such as the rating scale and analysts' consensus recommendations are introduced. Subsequently, the reason why the Belgian stock market was chosen as a reference is enlightened alongside with the data

selection process. Lastly, the methodology of the empirical research is explained step by step, from descriptive statistics, over the portfolio construction process, to the performance evaluation.

Section 4 commences by describing the data we are dealing with, which is followed by a presentation and a discussion of the results of the empirical research.

In section 5 the results are summarized and a conclusion finishes this paper.

2 Literature Review

This chapter lays out the most important research investigating the investment value behind analyst recommendations. In the past different methodologies have been used and different variables have been considered. Some researchers focused on absolute recommendation levels, while others investigated the predictive power of changes in recommendations and yet others pointed out factors amplifying the forecasting ability of analyst's recommendations. To assess the impact of those variables on future returns, the researchers used different methodologies and measured their impact on different kind of depended variables, such as the price fluctuations or post recommendation drifts. Beside demonstrating their main research objective, other interesting discoveries were made in the process such as the striking ratio of buy-to-sell recommendations, the reactions in trading volumes, the post recommendation drifts, etc.

Previous researchers, for example Stickel (1995), Womack (1996), Barber et al. (2001) and Barber and Lehavy (2003), have consistently shown that investors are able to find value in analyst recommendations and that strategies based on analyst recommendations can beat the market. However, these findings are disputed, especially when considering the impact transaction costs have on return figures.

The following section gives an overview of the existing literature relative to this subject organized by major theories or discoveries with respect to analyst recommendations.

2.1 Efficient Market Hypothesis

The efficient market hypothesis was developed in 1970 by Eugene Fama (1970) and states that share prices reflect all available information and therefore consistent alpha (excess return) generation is impossible. This hypothesis implies that there are no arbitrage opportunities, making it impossible for investors to buy undervalued stocks or sell overvalued stocks. As a result, it should not be possible for investors to outperform the market through superior stock picking abilities or market timing skills. Proponents of the efficient market theory firmly believe that the stocks trade consistently at their fair market value. If this theory would indeed be correct, the immense sums spend to remunerate security analysts would be wasted, since they should in theory not be able to predict future stock price increases or decreases. The theory indicates that once information is available to the public, a positive or negative news release about a company will not impact the security's price. The same applies to analysts' recommendations. Nonetheless, the analysts' work increases market efficiency since they serve as a middleman, disseminating information about an individual company to the broader public. The latter is especially true when considering complicated business models or companies active in industries that require deep understanding of complicated concepts, such as in the technology or biotechnology sector. This assumption has been investigated by Su et al. (2019) who discuss the price reactions following analyst recommendations on securities in the United Kingdom with special attention pointed to an industry-based analysis. Their analysis showed that analysts' downward revisions in two high-tech sectors, i.e., the Health Care and Technology sectors, generated significantly negative net abnormal returns, whereas this was not the case for the aggregate market. Su et al. explained this by associating high-tech companies with more complicated information, which provides sell-side analysts with an edge over non-institutional investors, since they are able to benefit from superior extertise.

In 1993, Alfred Cowles contributed unknowingly to the later developped efficient market hypothesis by demonstrating that investors were on average not able to outperform the market and that analysts were not able to recommend stocks that would deliver higher returns than their respective indicies. Various other studies showed similar findings and consequently Fama (1970) developed three forms of market efficiency within his theory. In the weak form, investors can not predict future price fluctuations by analyzing past prices. This form, however, leaves space for investors to take actions from fundamental analysis. The semi-strong form suggests that security prices reflect all publicly available information in a timely manner, making it impossible to earn excess returns from detaining information after it has been disclosed to the public. The last form is the strong efficiency, which treats insider information and implies that prices reflect public and private information at all time. Hence, one could say that Cowles research supports the semi-strong market hypothesis since he proves that analysts' recommendations do not add any value for investors.

Opponents of the strong market hypothesis, however, suggest that it is possible to beat the market and that stocks can deviate from their fair market value, making the money spend on analyst recommendations reasonable expenditures. Those researchers reject the strong and semi-strong form of market efficiency and give analysts a reason for existence. Amongst those are Stiglitz and Grossman (1980) who argued that the market is not perfectly efficient and prices do not reflect all available information. Their study proposes that access to information is costly and that consequently prices cannot reflect all available information. Their reasoning implies that positive returns are necessary to compensate for the costly endeavor of collecting and analyzing information. Additionally, they argue that analysts take over the important role of a middleman between companies and investors, whose role it is to convey information to the broader public. If, however prices would account for all available information, security analysts would receive no compensation for their activity and would have no reason for existence. These arguments suggest that the time and money analysts spend on security analysis present a value for investors.

2.2 Reliability and objectivity of Analysts

As discussed, security analysts serve as an intermediary who gathers information from a company and the market and conveys this information in form of research reports, earnings estimates or recommendations to investors and other market participants. Generally, research analysts specialize in specific industries and provide regular insights into a firm's financials. Besides, they frequently have access to more privileged information, such as a company's suppliers and customers and other resources within the industry. This makes them able to release research reports, financial estimations and a recommendation on the companies expected stock price. From an investor's standpoint, this set of information could be extremely valuable if the research is carried out without any bias. However, several biases have been exposed and studied in literature. Some of them are behavioral and others consequences of conflicts of interests involving themselves or tied to the establishments they work for.

Research has shown repeatedly that analysts tend to be reluctant to issue negative stock recommendations (e.g. Stickel [1995], Womack [1996], Barber et al.[2001], and Jegadeesh et al., [2004]). Subsequently, this makes them stand out and negative recommendations attract more attention than their positive counterparts. Barber et al. state that an incorrect Sell or even Strong Sell recommendation is more likely to affect an analyst's career than a false positive recommendation. From a behavioral aspect, this urges security analysts to be especially careful when disseminating negative stock recommendations, hence they are less frequent. Besides, there seems to be a general optimism among researchers, which steers them to publish more favorable recommendations as has been well-documented by Howe et al. (2009).

The uneven balance between positive and negative recommendations is not debatable and can be found in every study on this subject, no matter the industry or the stock market studied. In 1995, Stickel detected that his sample contained 55 percent positive recommendations, 33 percent neutral ones and only 12 percent negative recommendations. Similar observations have been made by Womack (1996) whose sample registered a ratio of a buy-to-sell recommendations of 7 to 1. Even more striking is the unevenness of the sample in the year of 2000 within the study of Barber et al. (2003), which consists of 72 percent positive recommendations and only 2 percent negative recommendations. Those studies, mainly conducted on US markets, are supported by the evidence of other studies that have been carried out on smaller markets, such as a study of recommendations of Italian companies (Cervellati et al., 2005), companies based in the UK (Su et al., 2019), and Indian stocks (Chatterjee et al., 2020). Also supporting this evidence, but less pronounced is a research of analyst recommendations on German stocks carried out by Souček and Wasserek (2014) whose sample consists of 42 percent favorable recommendations, 40 percent neutral and 20 percent unfavorable recommendations. As a consequence, this uneven distribution between buy and sell recommendations makes negative recommendations more valuable for investors.

Another bias which partially explains this tilt towards positive recommendations is tied to the fact that analysts frequently work for brokerage firms, which in turn have an underwriting relationship with a company. Most sell-side analysts work for brokerage firms whose primary income is earned through investment banking and not the release of security research. This could result in the analysts being forced to publish rather favorable recommendations in order to secure brokerage privileges with the covered company.[1] Therefore one could argue that analysts are pressured into being optimistic about certain companies in order to maintain good relationships with them, which

[1] The Amendments to NASD Rule 2711 and NYSE 472, enacted in May, 2002, require brokerage firms to disclose the percentage of securities rated Buy, Hold or Sell. This regulation's aim is to provide investors with more valuable information by enhancing the transparency of analysts' output (Dong and Hu, 2018). Following that enactment, optimistic recommendations have become less frequent, and the issuance of negative recommendations has since increased (Barber et al., 2006).

is even more true for private companies considering going public and henceforth securing a position as the lead underwriter (Lin and McNichols, 1998). Thus, analysts face a trade-off between publishing reliable research reports to defend their reputation and the necessity to secure and maintain a solid relationship with the covered firms.

The SEC[2], not unaware of these biases, condemned them and claimed that the conflicts of interest analysts are facing resulted in a reluctance to downgrade buy-rated stocks, particularly during the early 2000s. In their paper, Barber et al. (2007) investigated this claim and compared stock recommendation performance of investment banks and independent research firms. The researchers argue that if this statement is true, then banking analysts who were issuing buy recommendations in cases where hold or sell recommendations should be issued would ultimately underperform recommendations of independent research firms. Consequently, when issuing less favorable recommendations, they are likely to reflect truly unfavorable news and as a result these recommendations should earn more negative returns than those of independent research firms. When assessing their results, the initial assumptions turn out to be correct. Independent research firm's buy recommendations (upgrades to buy and strong buy) outperform those of investment banks by a significant 3.1 basis points per day (almost 8 percent annualized). On the other hand, the predictive power of hold/sell recommendations (downgrades to hold, sell or strong sell) of the investment banks outperforms those of independent research firms by significant 1.8 basis points a day (4.5 percent annualized). These results confirm the claim of the SEC and suggest that investment banks seemed to be reluctant to downgrade stocks that have low prospects during the bear market of the early 2000s.

With these biases in place an investor could be unwilling to put any faith in analysts' recommendations or earnings estimates. But generally, security analysts still deliver valuable information to market participants and they remain well respected entities among financial experts. To put this assumption to the test, Loh and Stulz (2011) attempt to measure the portion of analysts' recommendation changes that have a significant impact on stock returns. The researchers define

[2] The SEC also known as the U.S. Securities and Exchange Commission is an independent federal government regulatory agency. Its main aim is the protection of investors, maintenance of a fair and orderly functioning securities market and the facilitation of capital formation.

recommendation changes as influential if the two-day cumulative abnormal return is in the correct direction and statistically significant. After having analyzed 154,134 recommendations, they have observed that 11.7 percent of all recommendation changes are influential in returns and 12.8 percent are influential in turnover. Hence, one could argue that it is not interesting for investors to put any belief in analysts' opinions. The following subsection examines the real interest behind these recommendations and reviews the literature covering price responses to analyst recommendations.

2.3 Price responses to analyst recommendations

To assess the analysts' forecasting abilities many researchers dove into the topic and analyzed the impact analyst recommendations have on stock prices. After Cowles showed that only one third of publications made successful recommendations, many studies followed showing contradictory findings to what Cowles found in 1933.

These research papers can be divided into two main categories, the first one investigates the impact of upgrades and downgrades and the second one studies the effect on the stock price of new recommendations without considering their former rating. Within those two groups, some researchers analyzed individual recommendations, whereas others analyzed the aggregated consensus recommendations.

In the first group, researchers most commonly classify upgrades as upgrades to Buy or Strong Buy and Downgrades as downgrades to Sell or Strong Sell with slight variations from research to research. Most of the studies do not allow a direct comparison since some key factors are distinctive to each study, such as the time span during which the impact on the prices is measured or the reaction time to new recommendation issuances.

Elton, Gruber and Grossman (1986) examined the information contained in analysts' recommendations and paid special attention to changes in recommendations. They obtained significant excess returns for upgrades and downgrades. Considering a period of three years and analyzing over 10,000 forecasts they discovered that upgrades generated excess returns of 2.43 percent in the month of the recommendation change compared to stocks that were downgraded. This excess return decreased to 1.86 percent after one month following the change in recommendation. The latter would suggest that the impact recommendation changes have on prices is centered on the issuance of the new recommendation.

Womack (1996) analyzed recommendation changes from and to the extremes over a period of three years. Womack discovers a 3 percent increase for added to buy recommendations and a drop of 4.7 percent for added to sell recommendations in the three-day event period. These results support the claim of Juergens (1999) who found comparable return figures and concluded that upgrades have an inferior impact on prices than downgrades.

Stickel (1995) found similar evidence on a comparable sample size and registered an average of 1.2 percent price increase in the 11 days following an upgrade and a decrease of 1.3 percent for downgrades over the same time horizon. This, compared to the results of Womack (1996) would again suggest that price fluctuations are most pronounced at the event-time and fade away rather quickly.

Alike, Green (2006) studies the magnitude of price fluctuation after ratings have been up- or downgraded, but opposed to Elton et al. and Stickel, Green analyzes a much shorter, two-day period centered on the recommendation change. Changes in the price of stocks are measured from the close of the trading day before the recommendation change is issued to the close of the trading the day after. The mean price response in this two-day window is 5.74 percent for upgrades and –8.81 percent for downgrades. Compared to the event-period results showed by Womack (1996), Green's observed price responses are nearly twice as large. However, the two-day price response after clients have received the information and before it is spread to the general public is 1.7 percent for upgrades and –1.9 percent for downgrades. This means that having early access to new recommendations is key and that the bulk of price fluctuations happens immediately. Green's study digs deeper into this theory as he analyzes specific reaction times to recommendation releases. After including transaction costs, purchasing within the first five minutes of trading after a pre-market recommendation change is issued and selling the next trading day between 2:00 pm and 4:00 pm yields an average return of 1.02 percent. Delayed purchasing erodes returns and profits become insignificantly different from zero when buying after 12:00 pm. Selling short stocks that have been downgraded over the same period of time yields an average return of 1.50 percent but waiting 5 minutes already reduces the return by 0.62 percent. Selling short after noon does not yield returns significantly different from zero. When it comes to a longer horizon, abnormal returns one month following an upgrade are 1.40 percent and 2.59 percent using the size-industry adjusted returns and the three-factor model respectively. At the three- and six-month horizons results achieved with both models are not consistently yielding positive returns. When considering negative recommendation changes, abnormal returns one month following a downgrade are negative but only significant for the size-industry adjusted returns (–0.99 percent). At the three-month horizon, both abnormal return figures are negative and significant; the average size-industry adjusted returns are –4.10 percent and the three-factor abnormal returns are –1.26 percent. At the six-month horizon only the size-industry adjusted returns of –5.37 percent are significant at the 1% level. Green's findings are supportive of the previous research and imply that it is imperative to act quickly to benefit the most from new recommendations. Additionally, it seems that downgrades have a more persistent impact on stock prices and, therefore, they have more predictive power than upgrades.

The second group are made up of studies that focus on new recommendations without considering their relation to former ones. In 1999, Juergens findings show that the average 3-day cumulative abnormal return (CAR) for 2,049 positive recommendations is 1.91 percent, whereas the return for the full sample is –0.33 percent. On the other hand, negative recommendations yielded a significant 3-day CAR of –3.14 percent. Compared to the up- and downgrades that where analyzed as well in her study, she concludes that changes in recommendations are more predictive of future returns than new recommendations.

Similar conclusions are made by Jegadeesh et al., (2004), who examined two different trading strategies. The results of the study indicate that a strategy, which buys the quintile of stocks with the most favorable ratings and sells short the quintile with the least favorable ratings, yields a market-adjusted excess return of 2.3 percent over the following six months. The second trading strategy that buys stocks in the top *change in analyst recommendation group* (stocks that registered the highest upgrades) and sells short those in the bottom group, again with a holding period of six months, outperforms the first one and yields a market-adjusted excess return of 2.7 percent, suggesting that changes in recommendations have more predictive power than absolute levels. In Jegadeesh et al.'s opinion this finding suggests that either analysts bring information to the general public through their recommendation changes, which are a partial consequence of other signals, or the analysts create their own price momentum thanks to their prestige as "opinion makers".

The investment strategy used by Jegadeesh et al., (2004) was partially inspired by an earlier study conducted on consensus analysts' recommendations by Barber et al. (2001). Their research analyzes aggregate recommendations and tracks the performance of firms grouped into different portfolios based on the consensus analyst recommendation. In the sample period of this study, Barber et al. found that buying the first portfolio earns an annualized geometric mean return of 18.8 percent, whereas buying those stocks with the least favorable recommendations earns only 5.78 percent. In the same time period, the value-weighted market portfolio registered an annualized geometric mean return of 14.5 percent. When considering market risk, size, book-to-market, and price momentum effects, the first portfolio generates an annual abnormal gross return of 4.13 percent, whereas the fifth portfolio yields –4.91 percent. As a result, if one would purchase the first portfolio and sell short the fifth, one would generate an average abnormal gross return of 75 basis points (bps) per month. Including transaction costs reduces the annual return from holding portfolio 1 by 6 percent and as a result a strategy that consists in buying portfolio 1 yields a negative abnormal net return for all models ranging between –3.59 and –1.77 percent. Similarly, transaction costs associated with short selling those stocks with the least favorable recommendations offsets the annual return by 6.09 percent, which implies an abnormal net annual return that ranges from –1.18 to 1.55 percent. To minimize transaction costs the researchers explored the possibility to re-balance the portfolios less frequently, but the reduction in turnover that ultimately lowers the transaction costs is not enough to counterbalance the decrease in abnormal gross returns that comes with less frequent rebalancing. To further complement their study, Barber et al. investigated the influence investment delays have on the returns and found that the returns of portfolios with an increased investment delay steadily erode, which is consistent with the findings of Stickel (1995) and Womack (1996). Lastly, Barber et al. investigate the inconsistencies that could be pronounced in analyzing firms of different sizes. Their findings are that small stocks exhibit the highest portfolio 1 returns, at 6.90 percent annually and the lowest portfolio 5 returns at –11.1 percent annually. However, since the round-trip transaction costs are assumed to be higher for small firms, the abnormal net return of purchasing the most favorably recommended stocks or selling the least favorably recommended stocks becomes negative.

Two years later Barber, Lehavy, McNichols and Trueman (2003) reassessed the impact analysts' stock recommendations have on return figures after discovering the disaster of stock picking accuracy in the year 2000. For the period of 1996 until 1999, they observed a near-monotonic decrease in market adjusted returns moving from portfolio 1 (containing stocks with ratings of 1.5 or lower) to portfolio 5 (containing stocks with ratings of 3 or higher), which is comparable to the results of their prior study of 2001. The difference between the most favorable and the least favorable recommended portfolio was a significant 2.17 percent per month. However, when considering only the year 2000, the results are striking; the market-adjusted returns are monotonically increasing moving from portfolio 1 to 5. Furthermore, the monthly difference between the most and the least highly rated stocks was a significant –6.97 percent. Translated to annual returns, the most favorable recommended portfolio earned a negative annual return of –31.2 percent in 2000 and the least favorable recommended portfolio earned a positive annual return of 48.7 percent. The researchers alert their audience that excluding the results of the year 2000 could significantly impact the results of a study regarding analysts' stock recommendations.

To sum up this section, Table 1 summarizes they key numerical findings of the previously mentioned studies. As said earlier, we can clearly see that the returns associated with negative recommendations or downward recommendation changes are more pronounced and when focusing on specific studies (e.g. Juergens [1999] and Jegadeesh et al. [2004]) we are able to detect that changes in recommendations are more predictive of future abnormal returns than absolute recommendation levels. The results show clearly that analysts' recommendations present value for investors and guide them in the right direction.

Table 1

Overview of different return figures obtained from previous research

Table 1 provides a general overview of the different return figures resulting from the empirical research sections of the past literature. It re-groups the main results of some of the papers mentioned in the literature review and focuses on those observing the impact recommendations have on returns. It leaves out studies conducted before 1990 since the methodology and data is not comparable. Likewise, results that take into account other factors and variables are not considered.

Researcher	Explanatory Variables	Dependent variable	Time window	Observed result
Stickel, 1995	(1) Upgrades to strong buy (2) Downgrades to strong sell, sell and hold	Market-adjusted return	11 business days centered on the recommendation	(1) 1.16% (2) –1.28%
Womack, 1996	(1) Buy or Strong Buy (2) Sell or Strong Sell	Size-adjusted return	3-day window centered on the recommendation	(1) 3.00% (2) –4.70%
	(1) Buy or Strong Buy (2) Sell or Strong Sell	Post-recommendation drift duration & size-adjusted return	To be determined	(1) One month & 2.40% (2) Six months & –9.10%
Juergens, 1999	(1) Buy or Strong Buy (2) Sell or Strong Sell (3) Change from Hold to Strong Buy (4) Change from Strong Buy to Hold	Cumulative abnormal return (CAR)	3 days	(1) 1.91% (2) –3.14% (3) 4.14% (4) –5.39%
Barber, Lehavy, McNichols and Trueman, 2001	Consensus recommendation portfolios (1) Portfolio containing most recommended stocks (2) Portfolio containing least recommended stocks	Annualized abnormal gross return (defined by the 4 Factor model)	Portfolios are rebalanced daily (1985-1996)	(1) 4.13% (2) –4.91%
Jegadeesh, Kim, Krische and Lee, 2004	(1) Buy most recommended quintile & sell least recommended quintile	Market-adjusted excess return over the following 6 months	Rebalanced each quarter & holding period of 6 months	(1) 2.3%

	(2) Buy Changes to strong Buys and sell short Changes to strong sells			(2) 2.7%
Green, 2006	(1) Upgrade to Strong buy or buy (2) Any downgrade	Market-adjusted return	Close of trading day before recommendation and close after recommendation	(1) 5.74% (2) –8.81%

2.4 Post-recommendation drifts

As briefly mentioned in the previous subsection, several analysts observed post-recommendation drifts, their magnitude and their duration. In their study of 1986, Gruber et al. observed that excess returns already deteriorated after one month following a recommendation change. However, this assertion is overthrown in 1996 by Womack who discovers significant post-event drifts that are not mean-reverting. On the one hand, in case of a buy recommendation, the post-recommendation drift is significant but short-lived, with an incremental mean size-adjusted return of 2.4 percent for the first post event month beginning two days after the day the recommendation was recorded. On the other hand, sell recommendations are associated with more significant and more persistent post-recommendation drifts. The incremental mean size-adjusted return was found to be –9.1 percent for a six-month post event period.

Green's (2006) findings go in the same direction but it seems that price reactions following upgrades seem to be slightly mean-reverting. He registers positive returns for upgrades in the month following the recommendation change, but those become less pronounced after this first month. In the case of downgrades, he observes more persistent and pronounced negative returns following the issuance of the recommendation and the trend appears to persist for over six months.

Loh's (2010) study adds to the post-recommendation drift literature by investigating investor inattention and the underreaction to stock recommendations. He assumes that if investors initially neglect the additional information that is brought to the market by recommendations, a drift in the stock price follows during the time when investors incorporate this information. Additionally, Loh tests if there is a difference in reaction for low-attention stocks and high-attention stocks. The level of attention investors are giving to a stock is measured by the prior amount of trading in the firm's stock. At the event date (three-day window centered at recommendation) high turnover stocks see an average CAR of –4.13 percent for downgrades, while low turnover stocks only a CAR of –2.80 percent (a difference of 1.33 percent). On the other hand, for the most upgraded stocks the difference between low and high turnover stocks was less pronounced, being –0.13 percent. Regarding the post-recommendation drift, low turnover stocks experience larger drifts. The average CAR from day two until day 42 (two-month horizon) for the most upgraded stocks minus the most downgraded stocks is 1.26 percent for high turnover stocks, while it is 2.77 percent for low turnover stocks. For all studied timespans (1 month, 2 months and 3 months) the observed underreaction is significantly higher for low-turnover stocks and therefore the drift is more pronounced. Additionally, it can be observed that for high turnover stocks a larger fraction of the return associated with recommendation changes occurs at the event date. Loh concludes that investors would benefit from following the stock recommendations of firms to which the market is inactive, since they will be able to take profit from the drift in price that occurs when the market corrects the initial under-reaction.

Souček and Wasserek (2014) who investigated the German market also discovered post-recommendation drifts but opposed to prior literature their drifts following positive recommendations are of longer duration than those of negative recommendations. They find that the post-recommendation drifts are not mean-reverting and persistent for up to six months for upgrades and four months for downgrades.

2.5 Distinctive features that make recommendations influential

After reviewing existing research, it seems that recommendations do present valuable advice for investors, this, however, becomes debatable when including transaction costs. Nevertheless, most studies share some common outcomes. Firstly, the ratio between buy and sell recommendations is significantly leaning towards buy recommendations and therefore added-to-sell recommendations are on the one hand less frequent but on the other hand more predictive. Another finding that most researchers agree upon is the superior forecasting ability of recommendation changes (upgrades and downgrades, especially changes to the extremes), which are able to better predict future returns than absolute recommendations. Another shared finding, which seems intuitive, is that transaction costs have a large impact on investment strategies, especially for transaction intensive strategies such as the one developed by Barber et al. (2001). To further complement this idea, some researchers (e.g., Barber et al. [2001] and Green [2006]) tested the assumption of lowering the transaction costs by less frequent rebalancing of the investment portfolios, but the decreased transaction costs were not able to counterbalance the decrease in abnormal gross returns. Another finding is that the impact of recommendations on smaller companies is larger, however the transaction costs associated with lower capitalized firms is usually higher, which again offsets the additional gains (e.g. Womack [1996], Barber et al. [2001]). Furthermore, timely access to recommendation issuances is key and to achieve maximum returns, the reaction time has to be as quick as possible. Regarding the simultaneous release of recommendations and news, the results of Juergens' study (1999) showed that the event-time returns are more pronounced for those that are complemented by public news releases.

To further point out factors that make analysts' recommendations more predictive some researchers tested different variables to examine their influence on price variations. The most in-depth study in this particular area is the work of Stickel (1995) who identified factors that contribute to the short or long-term stock price performance following buy and sell recommendations. His analysis of factors that contribute to return amplifications indicates that:

- Upgrades to strong buy have a greater positive price effect than upgrades to buy. Downgrades to strong sell and sell have a greater negative price effect than downgrades to hold. These differences seem to be permanent.
- Changes in recommendations that skip a rank have a greater impact than those that do not skip a rank. This difference is only persistent around the event time and seems to disappear after some days. This finding is supported by the work of Souček and Wasserek (2014).
- Analysts who have better reputation have more influence on prices, yet this factor seems to be only temporary. However, this finding is contradictory to the findings of Elton et al., (1986) who tried to point out a difference in forecasting abilities between different brokerage houses. After conducting their analysis, they concluded that they were not able to identify superior brokerage firms or one firm consistently outperforming another one.
- Smaller companies show stronger reactions to recommendations than larger firms. This factor appears to be a permanent effect and is supported by other researchers (e.g. Womack [1996], Barber et al. [2001]).

- Lastly, recommendation changes that are issued around same-sign earnings forecasts have greater impact on the price of the underlying stock than other changes. This factor seems to be permanent and is supported by the work of Loh and Stulz (2011).

When combining all factors, the average excess return of a stock in response to a buy recommendation quadruples, from 1.16 percent to 4.61 percent over a period of 11 business days centered on the date the recommendation was issued. In case of a sell recommendation the return decreases from −1.28 percent to −5.29 percent when all factors are met.

Furthermore, Loh and Stulz (2011) point out that a quarter of analysts never released an influential recommendation change in their recommendation histories. Analysts that had influential recommendation changes before are more likely to be influential with their subsequent recommendation changes. Having more accurate earnings forecasts also contributes to being influential and recommendations moving away from the consensus and being released around the earnings forecast tend to be more influential. Further, the expertise and skill of the analyst, growth firms, small firms, high institutional ownership firms and low analyst activity firms are all factors that increase the chances for a recommendation change to be influential.

Lastly, Jegadeesh et al., (2004) investigated some fundamental features that most of the upgraded stocks had in common. They concluded that company with a relatively high (low) rating prior to a new issuance is more likely to be down (up) graded. Additionally, the data investigation shows that analysts issue higher ratings for "glamour" stocks than for "value" stocks.[3] Likewise, stocks with positive (earnings and price) momentum, high trading volumes, great past sales growth and high expected earnings growth tend to receive more favorable ratings from analysts.

2.6 Country specific studies

Most of the previously mentioned studies mainly focus on US equities and only few investigate the value of analyst recommendations in other markets. A study conducted by Souček and

[3] "Glamour stock" is a term used to characterize stocks by a high earnings growth rate and a price that increases faster than the market during bullish periods. The term "Value stock" is used to describe shares which trade at a lower price than its fundamentals (such as sales, earnings or dividends) would suggest.

Wasserek (2014) analyzes the impact of analysts' recommendations on the stock prices of the German DAX30 Index. Their findings show that at the announcement date, the average return for upgrades is 0.727 percent and −0.678 percent for downgrades. To incorporate the delay in time small investors exhibit when reacting to new information, they re-asses their results including a one-day delay in their computations. After doing so, only few investment strategies yield abnormal returns significantly different from zero.

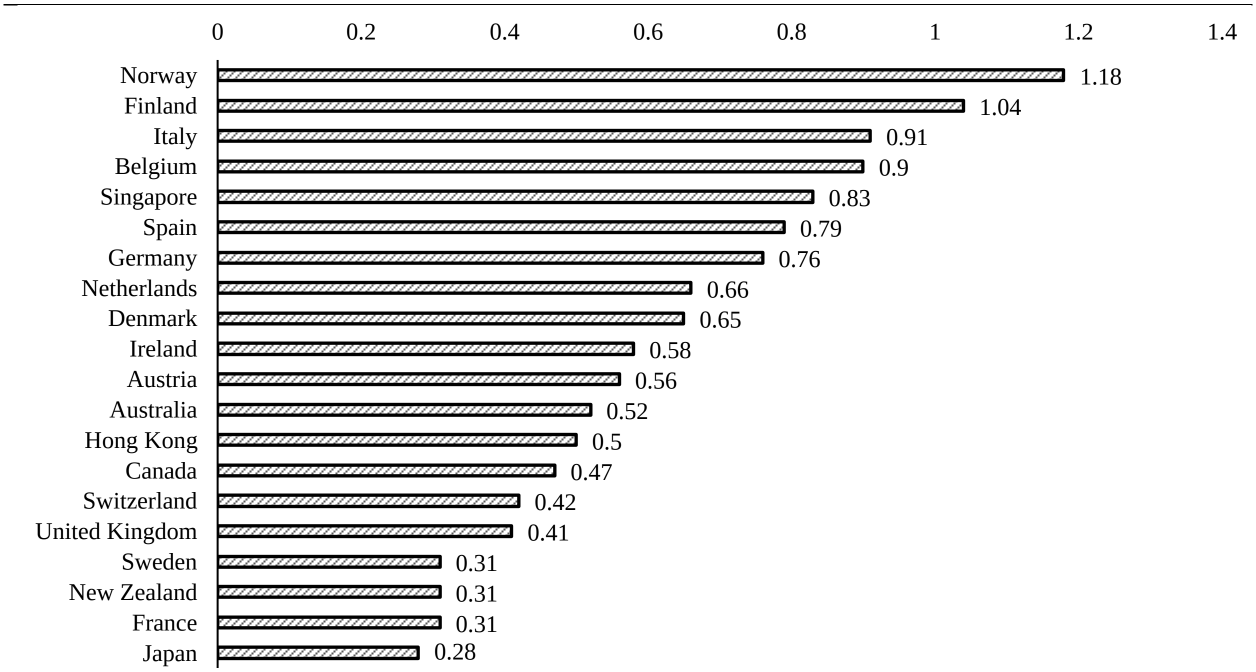
Another study endorsing analysts' recommendations is the work published by Cervellati et al. (2005) who sorted companies listed on the Italian Stock Exchange every quarter into 5 portfolios based on analysts' consensus to calculate the excess returns of each portfolio in each quarter. In the period from 1999 to 2004, the portfolio that comprises the stocks that have received the best consensus yields a cumulative abnormal return of 4.24 percent, while the portfolio that comprises the stocks with the least favorable recommendations yields a cumulative abnormal return of −12.37 percent. Surprisingly, the portfolio, which includes stocks that have received a neutral recommendation, yields a cumulative abnormal return of −4.55 percent. They conclude that this seems to be an effect of investors acknowledging the uneven ratio of buy-to-sell recommendations and the conflict-of-interest analysts face, especially when negative recommendations can harm the relationship between the analysts' firm and the covered company.

Su et al. (2019) investigate the value of analyst recommendation revisions in the UK and their findings show little usefulness when it comes to recommendations on UK-based companies. Their research investigates a first portfolio that includes stocks that have been upgraded to a Buy or Strong Buy recommendation and second portfolio that includes stocks that have been downgraded to a Hold, Sell or Strong Sell recommendation. The portfolios are rebalanced daily and stocks are dropped if a brokerage house issues a recommendation that isn't conform to the portfolio's characteristics. They conclude that upgrades are valueless in the UK and that investors are not able to generate positive abnormal returns by investing in upgraded stocks. However, their findings also suggest, that downward revisions present investment value for investors, that is however not exploitable when accounting for transaction costs.

Lastly, a very recent study published by Azevedo and Müller (2020) re-examines the value of analyst recommendations in 45 separate countries. For each country the researchers sort stocks into quintiles based on the consensus recommendation the stock received in the previous month. To evaluate the performance of the recommendations, the fifth quintile is subtracted from the first and then the equally-weighted returns are computed. This long-short strategy generates a monthly equally-weighted raw return of 0.58 percent (with a t-statistic of 5.05) in worldwide stock markets excluding the U.S. Interestingly, the value-weighted raw return of the same long-short strategy in the U.S. market is –0.02 percent, which turns out to be a significant outlier when considering other developed markets. When it comes to the country specific data, the study goes in depth by analyzing 45 countries individually. Some of the study's findings (those for some developed markets) are re-grouped in Figure 1 displaying the monthly equally-weighted raw returns of the long-short strategies for some of the individual markets studied in this research. What is particularly interesting with respect to this study, is the fact that the long-strategy buying the most favorably recommended stocks and shorting the least favorably recommended stocks of the Belgian market was able to earn a monthly equally-weighted raw return of 0.9 percent (significant at a 1 percent level) and is thus amongst the highest obtained raw returns in this study.

Figure 1

Monthly equally-weighted raw returns (%) of long-short strategies based on consensus recommendations



3 Research Methodology

The following section serves as an introduction to the quantitative research discussion of this paper. First, the data utilized is introduced alongside some specifications on consensus recommendations and the rating scale. Second, a subsection is devoted to explaining why this research focuses on the constituents of the Belgian BEL20 stock index. Finally, the research design is explained in detail.

3.1 Rating Scale and Analysts' Consensus Recommendations

Stock recommendations have been issued by many different brokerage houses and other financial institutions throughout time. Hence, these analysts' recommendations come in various forms. Most of them are issued on a five-point scale; ratings from 1 to 1.5 are labelled as "Strong Buy"; ratings from 1.5 to 2.5 are referred to as "Buy"; "Hold" is associated to recommendations having a rating between 2.5 and 3.5: ratings between 3.5 and 4.5 are labelled as "Sell"; and ratings from 4.5 to 5 are referred to as "Strong Sell". To avoid misunderstandings, this will be the labeling used throughout this paper. However, different brokerage houses use different scales and labels for their recommendations, and as a result "Outperform", "Attractive", "Overweight", "Accumulate", and some others are synonyms used for "Buy" recommendations. Since this paper analyzes the consensus recommendations and not individual recommendations, we are mostly interested in the numerical ratings associated with the recommendations.

The analysts' consensus recommendation for stock *i* at time τ denoted by $C_{i\tau}$ is the arithmetic mean of all currently outstanding recommendations for this stock.

$$C_{i\tau} = \frac{1}{n_{i\tau}} \sum_{j=1}^{n} A_{ij}, \tag{1}$$

where

$C_{i\tau}$ = the analysts' consensus recommendation of stock *i* at time τ,

$n_{i\tau}$ = number of outstanding recommendations on stock *i* at time τ, and

A_j = the recommendation of analyst *j* on stock *i*.

3.2 Domestic Market

As opposed to the existing literature on this topic, this study focusses solely on analysts' consensus recommendations for Belgian stocks, more specifically for those stocks that shape the BEL20 index. This study adds to the literature in the sense that previous research has been conducted mostly on U.S. stocks (e.g. Womack [1996] or Barber et al. [2001]).To my knowledge the only other study conducting research specifically on the Belgian market is the recently published work of Azevedo and Müller (2020).

Besides, there seems to be a preference for local equity, which influences investors to ignore the well-documented benefits of international diversification and pushes them to invest in domestic companies.[4] This behavior is a well-studied topic and driven by several factors. On the one hand, these factors seem to be behavioral; as shown by Strong and Xu (2003) and by French and Porterba (1991). Amongst others they identify a significant optimism of asset managers towards their home equity market and discover that asset managers' expectations about their home market is significantly higher than those for foreign markets. On the other hand, Coval and Moskowitz (1999) discuss that this *Home Bias* could be attributed to the ease of access to information. In their study they identify that local equity preference is strongly linked to firm size, leverage, and output tradability. Developing these findings further, they find that locally held firms tend to be small, highly levered and seem to sell their goods locally. These firms are exactly those for which one would expect investor information to be rather limited for international investors. Therefore, holding this information is even more valuable for local investors and they are urged to act upon this material.

To acknowledge this *Home Bias* and to add to the current literature it is of interest to test the value of analysts' consensus recommendations with respect to the constituents of the BEL20 index.

The BEL20 is the most used stock index to reflect the performance of the Belgian stock market. The index was first introduced in 1991 and mirrors the performance of the 20 largest shares listed on the Euronext Brussels since then. The best represented sectors in 2020 are Banking and Health Care with a weight a little over 20 percent each, followed by Food & Beverage with 13 percent.

[4] Grubel (1968) and DeSantis and Gerard (1997) exhibited significant benefits from international diversification.

3.3 Data Selection

The data used to conduct the empirical research of this paper was retrieved from several sources. In order to include all sorts of historical events, economic cycles, as well as major bear and bull markets into the study, I decided to conduct the research over a period of 15 years and 9 months, starting in January 2005 and ending in September 2020. As discussed in the previous subsection, the data selected encompasses solely the figures related to the historical constituents of the BEL20 index throughout the studied sample period.

Firstly, the analysts' consensus recommendation data was retrieved from Thomson Reuters' Eikon database. The data on Eikon is conform to the Institutional Brokers' Estimate System (I/B/E/S) and the collected data is ranked on a scale from 1 to 5, where 1 is a Strong Buy, 2 a Buy, 3 a Hold, 4 a Sell, and 5 a Strong Sell.

Second, most historical stock prices were obtained from Investing.com and Yahoo Finance, those of delisted companies that once figured in the BEL20 index were retrieved from Thomson Reuters' Eikon database if available, if not the stocks were omitted from this research.[5] I used the close prices instead of the adjusted close prices since this study's main focus are the capital gains and not dividend gains. Additionally, this measure allows better comparability to the market, since the BEL20 Index or the BEL All Shares Index (which is chosen to represent the market) do not account for dividends of their components in their prices. I chose to use normal returns instead of log-returns to allow a simple and direct interpretation of the obtained return figures, which is not the case for log-returns. Besides, since a log-return is a continuously compounded rate over time, it is not possible to sum log-returns of different stocks in a portfolio to get the total portfolio return. If one would do so with log returns, one would not add the returns together but compound them.

The individual stock returns are given by the following formula:

$$R_{\mathrm{i}\tau} = \frac{P_{\tau} - P_{\tau-1}}{P_{\tau-1}}, \tag{2}$$

where

[5] Fortunately, the data of most delisted companies was still available and therefore only three companies were excluded from the sample. These are Almanij (in the index until March, 2005), Aurubis Belgium (in the index until May, 2005) and Electrabel (in the index until November 2005). Hence, these omittances do not influence the results notably since the omitted stocks only account for 16 months in total.

$R_{i\tau}$ = the return of the stock i on date τ, and

P_{τ} = the price of stock i on date τ.

3.4 Research Design

The main and most important part of this paper is the empirical research. To test the hypothesis of this research it is crucial to examine the data carefully and to proceed step by step.

The following subsections will elaborate on the methodologies used in the research part of this master thesis. First, the data is examined over a time span of over 15 years and analyzed using descriptive statistics. In a second step, the different portfolios are constructed as a function of the consensus recommendations of the stocks. Finally, the performance of each portfolio is computed and examined to test if it is possible to generate abnormal returns while using consensus recommendations as an investing strategy.

3.4.1 Descriptive Statistics

The first step of the empirical research is to analyze the complete dataset used in this study over the whole sample period. In the first part of this subsection, the different components that made up the index are described with some key figures.

The use of some descriptive statistics will give us a first impression of the data we are dealing with. First, I'll review the analysts' average consensus recommendations of the firms paired with their average monthly returns. Later, I'll display the evolution of the index and the average consensus rating of the whole sample. This shall give us a first idea of the Belgian stock market during our sample period and we can trace the development of the recommendations alongside their actual performances over time.

3.4.2 Portfolio Construction

To determine the returns associated with the consensus recommendations, the stocks are divided according to their given recommendations. Each of the companies listed on the BEL20 will be figuring in one of four different calendar-time portfolios based on the analysts' consensus recommendations.

Having retrieved the daily consensus recommendations from Thomson Reuters Eikon database the calendar-time portfolios are constructed as follows; each company *i* is placed in a portfolio at the close of each trading on date $\tau-1$ based on its consensus recommendation $C_{i\tau-1}$. Literature has shown the timing of an investor's reaction to recommendation changes is crucial (e.g. Green [2006]), but since this study focusses on the average recommendation of a stock and does not incorporate individual recommendations and therefore no changes, I will follow Souček and Wasserek's (2014) reasoning and use a more investor-oriented approach, which incorporates a delay in time. Therefore, the portfolios are re-balanced at the end of each trading day and not at the exact moment a new recommendation is issued. This would give the investor time to absorb the news and recommendation changes analysts made during the day.

In their study, Barber et al. (2001) constructed five different portfolios with small brackets at the favorable end of the rating scale and with a much larger bracket of the other end since they observed fewer negative recommendations than positive recommendations in their sample. The reasoning behind this separation of the portfolios seems somewhat arbitrary, but this separation achieves a high degree of separation across the five portfolios in the case of their study. Their portfolios were built as follows; the first portfolio comprises the most favorably recommended stocks, those for which $1 \leq C_{i\tau-1} \leq 1.5$; the second portfolio contains the stocks with the second highest average recommendation, those for which $1.5 < C_{i\tau-1} \leq 2$; the third consists of stocks for which $2 < C_{i\tau-1} \leq 2.5$; the fourth contains stocks for which $2.5 < C_{i\tau-1} \leq 3$; and the fifth and last portfolio comprises the stocks that have the least favorable consensus recommendation, those for which $C_{i\tau-1} \geq 3$. In the case of this research, these brackets would not achieve a high degree of separation between the portfolios since most of the stocks would be attributed to portfolio 3 and 4 and only very few would make up portfolios 1, 2 and 5. Additionally, since the sample contains only 20 stocks at a time, such a separation would leave portfolio 1 with 0.3 stocks and portfolio 2 with 1.9 stocks on average, which is not representative enough to further analyze these results. To obtain a somewhat similar number of stocks within each portfolio on each day, I will sort the 20 companies into quartiles based on their analysts' consensus recommendation. Therefore portfolio 1 will contain the first quartile of most recommended stocks, the second portfolio will contain the quartile with the next most recommended stocks, portfolio 3 contains the third quartile of most recommended stocks and portfolio 4 is made up of the quartile with the least recommended stocks.

This assures a relatively high and consistent number of stocks within each portfolio, which makes the extreme portfolios easier to interpret and further testing more reliable.

Once the composition of each portfolio p is determined at the close of trading on date $\tau-1$, the returns of the portfolios for date τ are computed. In this study, equally weighted returns are used to compute a portfolio's return. Consequently, the equally weighted return of portfolio p for date τ is denoted by $R_{p\tau}$ and computed as follows:

$$R_{p\tau} = \sum_{i=1}^{n_{p\tau-1}} x_{i\tau-1} \times R_{i\tau} \,, \tag{3}$$

where

$n_{p\tau-1}$ = the number of firms in portfolio p at the close of trading day $\tau-1$,

$x_{p\tau}$ = 1 divided by the total number of stocks in portfolio p at day τ, and

$R_{i\tau}$ = the return of the stock i on date τ.

Lastly, for each month t in the sample period, the monthly returns R_{pt} of portfolio p are computed by compounding the daily returns of portfolio p over the n trading days of the month:

$$R_{pt} = \prod_{\tau=1}^{n} \left(1 + R_{p\tau}\right) - 1. \tag{4}$$

3.4.3 Performance Evaluation

Once the different portfolios have been built and their returns have been determined, the next step consists in measuring their performance. This will allow us to determine whether a profitable investment strategy exists when following the analysts' consensus recommendations. To measure the performance, I will use 3 different forms of abnormal return figures. Before computing those, the market-adjusted returns for portfolio p in month t, is determined by subtracting the market return from the return of portfolio p ($R_{pt} - R_{mt}$) where R_{mt} is the return on the BEL All-Share index of month t. After having computed the market excess returns for each portfolio, I'll define three measures for abnormal return. The first one is determined using the theoretical framework of the Capital Asset Pricing model (CAPM), which assumes the markets to be efficient and investors to be rational.[6] In this framework we compute the following monthly time-series regression, which returns coefficient estimates of α_p and β_p:

$$R_{pt} - Rf = \alpha_p + \beta_p(R_{mt} - Rf) + \varepsilon_{pt} \,, \tag{5}$$

where

Rf = the return on the Belgium treasury Bond with a 10-year maturity as the risk-free rate,
α_p = the estimated CAPM intercept (Jensen's alpha),
β_p = the estimated market beta, and
ε_{pt} = the error term of the regression for month t.

The second measure for abnormal performance will be obtained using the three-factor model developed by Fama and French in 1993. This second model includes two additional factors to the market risk factor: the first additional risk factor accounts for size and the second accounts for value. The reason behind this is discussed in Fama and French's work "Common risk factors in the returns on stocks and bonds" (1993), stating that small stocks tend to have higher average returns than big stocks, and value stocks tend to have higher average return than growth stocks. This framework will evaluate the performance of the five portfolios with the following monthly time series regression:

$$R_{pt} - Rf = \alpha_p + \beta_p(R_{mt} - Rf) + s_p SMB_t + v_p HML_t + \varepsilon_{pt} \,, \tag{6}$$

where

[6] The CAPM was introduced by Treynor, Sharpe, Lintner and Mossin independently. Their respective papers were building on the modern portfolio theory introduced by Markowitz.

SMB_t = the difference between the month t returns of a value-weighted portfolio of small stocks and one of large stocks, and

HML_t = the difference between the month t returns of a value-weighted portfolio of high book-to-market stocks and one of low book-to-market stocks,

s_p = the coefficient-estimate for the size factor, and

v_p = the coefficient-estimate for the value factor.[7]

This second time-series regression returns coefficient estimates for α_p, β_p, s_p and v_p.

The last intercept test includes a fourth factor that accounts for the momentum effect. The reasoning for including this momentum factor in the regression stems from the work of Jegadeesh an Titman (1993). They demonstrated that stocks that performed well in the past yielded significantly higher returns over 3- to 12-month holding periods than stocks that performed poorly in the past. The measure of this momentum factor has been developed by Carhart in 1997. Incorporating this factor, the third regression used to measure abnormal performance is the following:

$$R_{pt} - Rf = \alpha_p + \beta_p(R_{mt} - Rf) + s_p SMB_t + v_p HML_t + m_p WML_t + \varepsilon_{pt}\ , \qquad (7)$$

where

WML_t = the difference between the equally-weighted month t average return of the firms with the highest 30 percent return over the 11 months through month t–2 and the equally-weighted month t average return of the firms with the lowest 30 percent return over the 11 months through month t–2, and

m_p = the coefficient-estimate for the momentum factor.[8]

[7] and [8] The factors used in this time-series regression are the factors adapted for European markets and were retrieved from Ken French's database.

This second time-series regression returns coefficient estimates for α_p, β_p, s_p, v_p and m_p. These coefficient-estimates will allow us to better asses each portfolio's characteristics and therefore better evaluate their abnormal return figures. A portfolio with a value of β_p higher (lower) than one indicates that the firms in this portfolio are more (less) volatile than the market. A value of s_p higher (lower) than zero means that the portfolio is composed of smaller (larger) firms. A portfolio with a value of v_p higher (lower) than zero is a sign that the stocks in this portfolio have a rather high (low) book-to-market ratio. Finally, a higher (lower) value of m_p indicates a tilt towards a portfolio containing stocks that, on average, performed well (poorly) in the past.

3.4.4 Investment Strategies

In the following subsection the previously obtained information will be used to construct investment strategies. The first and second strategies are long only. The first strategy is a replication of portfolio 1, whereas the second strategy is long in portfolios 1 and 2. Strategy 3 is a long-short strategy which buys the stocks in portfolio 1 and short-sells those in portfolio 4. The fourth and last strategy is long in portfolios 1 and 2 and short-sells the stocks of portfolio 4. To evaluate their performances different measures are evaluated to control for return but also for risk-adjusted measures. Amongst those are raw returns, abnormal returns, volatility measures and risk-adjusted return measures such as the Sharpe ratio and the Information ratio.

In a subsequent section, previously built different portfolios or strategies are compared to similar portfolios or strategies that additionally account for several factors. Amongst those factors are investor sentiment and the impact of recommendation changes. These comparisons are done to evaluate if the value of analysts' consensus recommendation is influenced by these factors.

4 Empirical Research Results

In the following section I will lay out and discuss the results of the empirical research. First, the data will be analyzed in order to get a clear view of the records we are dealing with. Second, the two sets of portfolios built based on analysts' consensus recommendations are portrayed with descriptive statistics. The succeeding subsection will be the key element of this research; in this part the different return figures of the previously built portfolio will be analyzed. The objective of this will be to assess the initial question - whether it is possible for an investor to benefit from the analysts' consensus recommendation on stocks figuring in the BEL20 index. Later on, different investment strategies, based on the previous findings are assessed and evaluated. And lastly, the value of a change in analysts' consensus recommendations and the impact of investors' sentiment on the value of recommendations is evaluated.

4.1 Descriptive Statistics

Firstly, I will introduce the companies figuring in this study, which are the historical components of the BEL20 starting in January 2005 until September 2020. Table 2 provides a general overview of the 20 stocks figuring in the BEL20 as of June 2020, indicating their MNEMO, the company name, the stocks principal exchange country, the sector the company operates in and the weight the stock takes in the index. Of those 20 stocks, 17 are exchanged on the Euronext in Brussels and only 3 are exchanged in Amsterdam. One can see that AB Inbev takes the largest weight in the index and is therefore the most influential. Second and third weightiest companies are ING and KBC. Hence, the Banking sector is the best represented with a weight of just over 21 percent. Next up, is the Health Care sector with around 21 percent as well, which is made up of 3 companies that are UCB, Galapagos and ArgenX. The third best represented industry is the Food and Beverage industry, which constitutes nearly 14 percent of the BEL20 and is only composed of AB Inbev. Other large sectors taking weights between 5 and 10 percent are *Chemicals, Financial Services, Real Estate and Insurance*.

Table 2

Components of the BEL20 (as of June 2020)[9]

The following table provides details of the 20 components of the BEL20 stock index. The table indicates the company's MNEMO, the company's name, it's principal exchange country, the sector and the weight (in percent) the company takes in the index. The companies are listed in apathetical order of their MNEMO.

MNEMO	Company	Country	Sector (ICB)	Weight (%) as of June, 2020
ABI	Ab Inbev	BE	Food & Beverage	13.67
ACKB	Ackermans van Haaren	BE	Financial Services	2.41
AED	Aedifica	BE	Real Estate	2.16
AGS	Ageas	BE	Insurance	6.3
APAM	Aperam	NL	Basic Resources	0.9
ARGX	Argenx SE	BE	Health Care	4.9
BAR	Barco	BE	Industrial Goods & Services	1.37
COFB	Cofinimmo	BE	Real Estate	2.72
COLR	Colruyt	BE	Retail	2.54
GBLB	GBL	BE	Financial Services	4.84
GLPG	Galapagos	NL	Health Care	7.08
INGA	ING Groep n.v.	NL	Banks	11.63
KBC	KBC	BE	Banks	9.77
PROX	Proximus	BE	Telecommunications	2.95
SOF	Sofina	BE	Financial Services	2.67
SOLB	Solvay	BE	Chemicals	4.25
TNET	Telenet group	BE	Media	1.17
UCB	UCB	BE	Health Care	9.3
UMI	Umicore	BE	Chemicals	6.21
WDP	Warehouse de Pauw	BE	Real Estate	3.15

[9] Data used from BEL20 Factsheet retrieved from live.euronext.com

The index's components are determined every year based on their market capitalization and therefore the composition of the index changes throughout the sample period. Table 3 provides information of the historical composition of the BEL20 during the analyzed sample period. The table encompasses all joiners and leavers throughout the studied timeframe, indicating the date they left or joined the index, their MNEMO, their principal exchange, their sector and the time during which they were part of the index.

Table 3

Joiners and Leavers of the BEL20 (January 2005 until September 2020)

The following table provides details of the joiners and leavers of the BEL20 stock index between January 2005 and September 2020. The table indicates the company's MNEMO, the company's name, it's principal exchange country, the sector, the date (yyyy-mm-dd) the company joined or left the index, and the total time the company was part of the index. If the companies were part of the index before January 2005, the date the company joined the index is omitted. The table is sorted by the time the company was part of the index.

MNEMO	Company	Country	Sector	Joined	Left	Total time in index
ABI	AB Inbev	BE	Food & Beverage	Pre 2005	-	15y 8m 28d
AGES	Ageas	BE	Life Insurance	Pre 2005	-	15y 8m 28d
COFB	Cofinimmo	BE	Real Estate	Pre 2005	-	15y 8m 28d
COLR	Colruyt	BE	Retail	Pre 2005	-	15y 8m 28d
GBLB	GBL	BE	Financial Services	Pre 2005	-	15y 8m 28d
KBC	KBC	BE	Banks	Pre 2005	-	15y 8m 28d
PROX	Proximus	BE	Telecommunications	Pre 2005	-	15y 8m 28d
SOLB	Solvay	BE	Chemicals	Pre 2005	-	15y 8m 28d
UCB	UCB	BE	Health Care	Pre 2005	-	15y 8m 28d
UMI	Umicore	BE	Chemicals	Pre 2005	-	15y 8m 28d
ACKB	Ackermans van Haaren	BE	Financial Services	2007-03-02	2020-09-30	13y 6m 30d
BEKB	Bekaert	BE	Industrials	Pre 2005	2018-03-19	13y 2m 15d
TNET	Telenet Group	BE	Media	2009-03-04	2020-09-30	11y 6m 27d
DELB	Delhaize LeLion	BE	Retail	Pre 2005	2016-07-25	11y 6m 22d
ENGIE	Engie	FR	Utilities	2008-07-22	2019-03-18	10y 7m 25d

OBEL	Orange Belgium	BE	Telecommunications	Pre 2005	2013-03-18	8y 2m 15d
DEXI	Dexia	BE	Banks	Pre 2005	2012-03-19	7y 2m 16d
BEFP	Befimmo	BE	Real Estate	2009-03-04	2016-03-21	7y 0m 17d
OMEP	Omega Pharma	BE	Health Care	Pre 2005	2011-12-29	6y 11m 26d
NAT	CNP SA	BE	Financial Services	2006-03-02	2011-05-02	5y 1m 30d
ELI	Elia Group	BE	Utilities	2012-03-19	2017-03-20	5y 0m 0d
BPOST	Bpost	BE	Freight & Logistics	2014-03-24	2019-03-18	4y 11m 24d
GLPG	Galapagos	NL	Health Care	2016-03-21	-	4y 6m 10d
INGA	ING Groep N.V.	NL	Banks	2016-03-21	-	4y 6m 10d
AGFB	Agfa Gevaert	BE	Industrials	Pre 2005	2009-03-04	4y 2m 1d
ONTEX	Ontex Group	BE	Consumer Products	2016-03-21	2020-03-23	4y 0m 1d
APAM	Aperam	NL	Basic Resources	2017-03-20	-	3y 6m 11d
SOF	Sofina	BE	Financial Services	2017-03-20	-	3y 6m 11d
DLL	Delta Lloyd	NL	Financial Services	2013-03-18	2016-03-21	3y 0m 3d
LOYE	Suez	FR	Utilities	2005-11-15	2008-07-22	2y 8m 5d
ARGX	Argenx	BE	Health Care	2018-06-18	-	2y 3m 13d
BAR	Barco	BE	Industrial Goods & Services	Pre 2005 2019-03-18	2007-03-02 -	2y 1m 29d
WDPP	Warehouse de Pauw	BE	Real Estate	2019-03-18	-	1y 6m 14d
NYR	Nyrstar	BE	Basic Materials	2007-10-30 2011-06-20	2009-03-04 2013-03-18	1y 4m 3d
IETB	D'Ieteren	BE	Consumer Cyclical	Pre 2005 2012-03-19	2006-03-02 2016-03-21	1y 1m 29d
OXUR	Oxurion	BE	Health Care	2013-03-18	2014-03-24	1y 0m 5d
AD	Ahold Delhaize	NL	Retail	2016-07-25	2017-03-20	0y 7m 24d
AED	Aedifica	BE	Real Estate	2020-03-23	-	0y 6m 8d
ABLX	ABlynx	BE	Real Estate	2018-03-19	2018-05-15	0y 1m 26d
ALMB	Almanij	BE	Financial Services	Pre 2005	2005-03-03	0y 2m 0d
CUMR	Aurubis Belgium	BE	Materials	Pre 2005	2005-05-02	0y 3m 29d
ELCB	Electrabel	BE	Utilities	Pre 2005	2005-11-15	0y 10m 13d

One can see that 9 companies stayed in the index for the whole sample period of over 15 years. In total, 42 companies shaped the index throughout the sample period of 15 years and 9 months. Of those 42 firms, 3 delisted companies are excluded from this study since their analysts' consensus recommendations were not available.

When observing the return figures of the different stocks and the index itself, whose evolution is displayed in Table 4, we can clearly identify some major trends that were shaped by main historic events occurring in the examined period. First and foremost, we can see that the BEL20 registered an annual return of –53.76 percent during the subprime financial crisis of 2008. In the subsequent year we can observe a rebound of the index, followed by slight drop in 2011. The next years are dominated by a strong overall performance until the last quarter of 2018, which saw most stocks in decline. The last notorious event is the bear market of early 2020 associated with the global outbreak of the Covid-19 virus.

Table 3 gives a more detailed overview on the relationship between the average monthly returns and the average consensus recommendation of the companies during their time in the index.

Throughout their time in the index ArgenX, Aedifica, Galapagos and Warehouse de Pauw had the highest average monthly return, with average return figures around 4.5 percent per month for ArgenX and Aedifica and monthly average returns around 2.7 percent for Galapagos and Warehouse de Pauw. The lowest average monthly returns during their time in the index are attributed to Nyrstar, Oxurion, Agfa Geveart and Dexia, having an average monthly return below –3 percent and in the case of Nyrstar the monthly average return is as low as –5.6 percent.

While having a look at the analysts' consensus recommendations, we can see that ArgenX, Oxurion, Galapagos and Ahold Delhaize have the most favorable average consensus ratings, which are below 2 on average during the time the companies were part of the BEL20. When comparing these observations to the return figures, the outcomes move in completely different directions leaving the observer questioning analysts' reliability. On the one hand, ArgenX's and Galapagos' average monthly return figures are among the highest 4 of the 39 stocks in the sample, but on the other hand, Ahold Delhaize and Oxurion have a significant negative average monthly return, Oxurion even having the second to worst average monthly return (–4.8 percent per month on average). Moving further, Nyrstar has the fifth best average consensus recommendation but the lowest monthly return of the sample.

The worst average ratings are associated with Dexia, Cofinimmo, Proximus and Colruyt, all receiving an average rating above 3.1 throughout their time in the index. When comparing the consensus ratings to their average monthly returns, one would expect to be confronted with negative values, but all except Dexia find themselves in the mid-range of the spectrum with returns between –0.26 and 0.57.

Table 3

Components Average Consensus Recommendation and Average Monthly Return (2005 to September 2020)

The following table gives an overview of the relationship between the average monthly returns and the average consensus recommendation of the companies during their time in the index. The table is sorted in ascending order of the average consensus recommendation.

Company	ARGX	OXUR	GLPG	AD	NYR	LOYE	BAR	AED
Avg. Cons. Rec.	1.66	1.84	1.87	1.96	2.05	2.09	2.13	2.14
Avg. Mon. Ret.	4.50%	–4.79%	2.87%	–0.76%	–5.61%	2.03%	–1.64%	4.50%
Company	APAM	INGA	OMEP	GBLB	ABI	ENGIE	TNET	KBC
Avg. Cons. Rec.	2.15	2.20	2.24	2.26	2.27	2.28	2.33	2.36
Avg. Mon. Ret.	–1.03%	–0.56%	0.49%	0.23%	0.80%	–0.66%	0.89%	0.73%
Company	ABLX	NAT	ONTEX	DLL	ACKB	BEKB	DELB	ELI
Avg. Cons. Rec.	2.40	2.46	2.46	2.46	2.46	2.47	2.51	2.52
Avg. Mon. Ret.	0.77%	0.20%	–0.90%	–1.67%	0.51%	0.88%	0.69%	0.79%
Company	IETB	UMI	AGES	AGFB	BPOST	OBEL	SOF	WDPP
Avg. Cons. Rec.	2.53	2.61	2.62	2.64	2.74	2.75	2.78	2.79
Avg. Mon. Ret.	1.29%	1.26%	0.19%	–3.97%	–0.60%	–1.10%	1.51%	2.64%
Company	UCB	SOLB	BEFP	DEXI	COFB	PROX	COLR	
Avg. Cons. Rec.	2.80	2.86	3.11	3.11	3.17	3.19	3.28	
Avg. Mon. Ret.	0.76%	0.28%	0.02%	–3.06%	0.13%	–0.26%	0.57%	

The average rating of all 20 stocks combined is close to 2.6, which would correspond to a split between a Buy and a Hold recommendation. This observation is in line with previous research that has shown repeatedly that positive recommendations are by far more common than negative ratings (e.g. Womack [1996], Stickel [1995], and Barber et al.[2001]). According to Barber et al. (2001) one explanation for this observation is that analysts are hesitant to publish negative stock recommendations, since there is a greater risk associated with disseminating pessimistic recommendations than with optimistic recommendations. Analysts that work for brokerage firms having an underwriting relationship with a company could be driven to publish rather favorable recommendations. From a more personal perspective, an incorrect Sell or even Strong Sell recommendation is more likely to affect an analyst's career than a false positive recommendation. This could be tied to the fact that unfavorable recommendations are disseminated less frequently and attract more attention from investors.

Analyzing relationships between the monthly or even the yearly returns and the consensus recommendations of individual companies seems to be difficult and thus I will proceed by examining the observations for the BEL20 as a whole, which should give us a first impression of the association between the consensus ratings and the returns associated to the stocks figuring in the index.

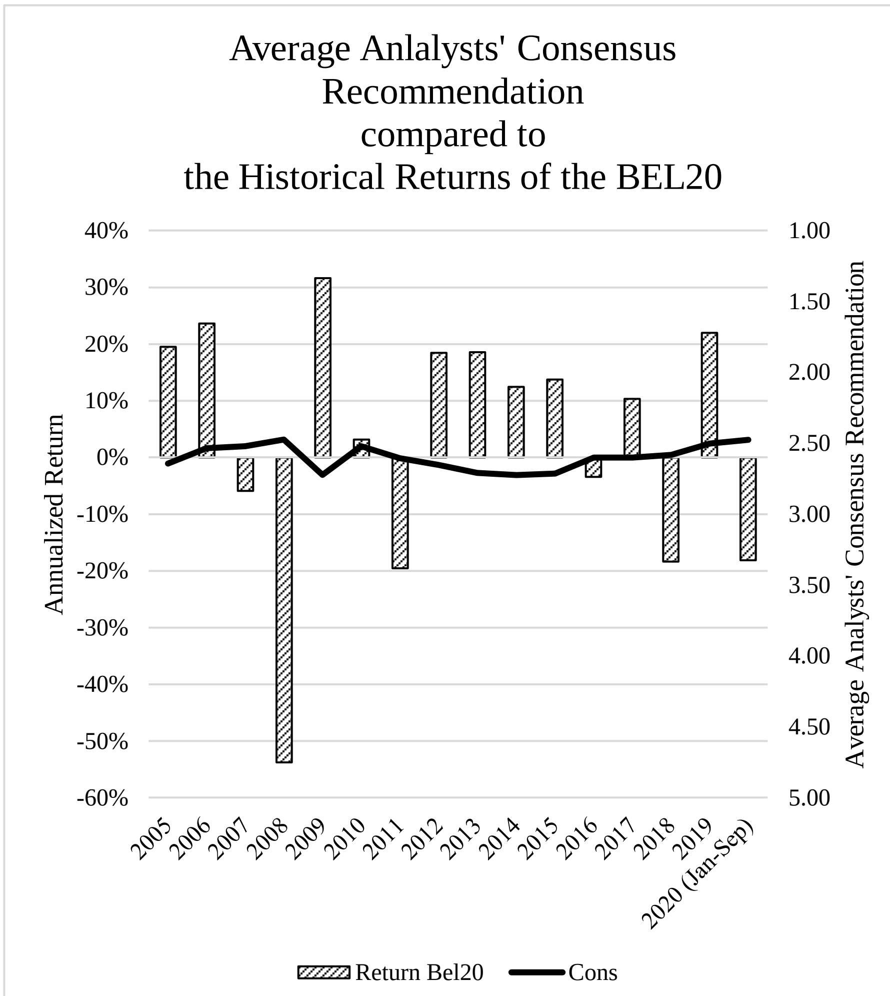
Table 4 shows us that there seems to be a slight delay in the consensus ratings, meaning that the ratings are on average revised to a less favorable recommendation after bear market conditions. This is consistent with the findings of Altinkiliç and Hansen (2009) who concluded their study claiming that analyst recommendations are often information free and follow large stock price reactions to corporate news and events. We can observe this trend best after the financial crisis of 2008 where the ratings drop in the following year. Surprisingly, it seems that recommendations have undergone a downwards trend during a bullish period beginning in 2012 until 2015 and started to increase again in 2016 until today. It is difficult to interpret these aggregated observations, since they are the result of many individual companies and therefore the results go in different directions in different periods. On the one hand, we can see favorable recommendations associated with high returns, while there are other periods were unfavorable recommendations are coupled with high returns and vice versa.

Table 4

Average Consensus Rating of the stocks figuring in the BEL20 compared to the annualized return of the BEL20, from 2005 to September 2020

The following table provides the yearly average analysts' consensus recommendation of the 20 stocks that figured in the BEL20 index throughout the sample period and the annual return of the BEL20 index itself. The scale of the ratings was inverted to ease the understanding, henceforth, more favorable recommendations are indicated higher than less favorable ones.

	Avg. Cons. Rec.	Ann. Return BEL20
2005	2.64	19%
2006	2.54	23%
2007	2.52	–6%
2008	2.48	–54%
2009	2.72	32%
2010	2.52	3%
2011	2.61	–20%
2012	2.66	18%
2013	2.71	19%
2014	2.73	12%
2015	2.71	14%
2016	2.60	–3%
2017	2.60	9%
2018	2.58	–18%
2019	2.50	22%
2020	2.48	–18%



4.2 Portfolio Characteristics

The first step of the empirical research is building the different portfolios based on the consensus rating of the twenty stocks throughout the sample period.[10] The portfolios were constructed as stated in the section *Research Design*.

Table 5 gives some descriptive statistics of the overall sample and a first impression on how the different stocks will later be sorted into the different portfolios. The histogram with the frequency of ratings already indicates that the method used by Barber et al. (2001) would not be able to populate the extreme portfolios enough to be relevant. Most of the stocks are centered around a consensus rating between 2 and 3 and only few observations can be attributed to extreme ratings, such as consensus recommendation below 1.5 or higher than 3.5. To ensure a representative number of stocks within each portfolio, the methodology sorting the stocks into quartiles is used. This methodology is the least subjective to arbitrary cut-offs since the stocks are sorted into quartiles on a daily basis based on their consensus rating of the previous day. One can see that the second portfolio contains slightly more stocks, this is due to the fact that if the total number of stocks is not always a multiple of four, the remainder of the division is allocated first to the second, then to the third and, if the remainder is three, the last portfolios have one stock more than the first portfolio.

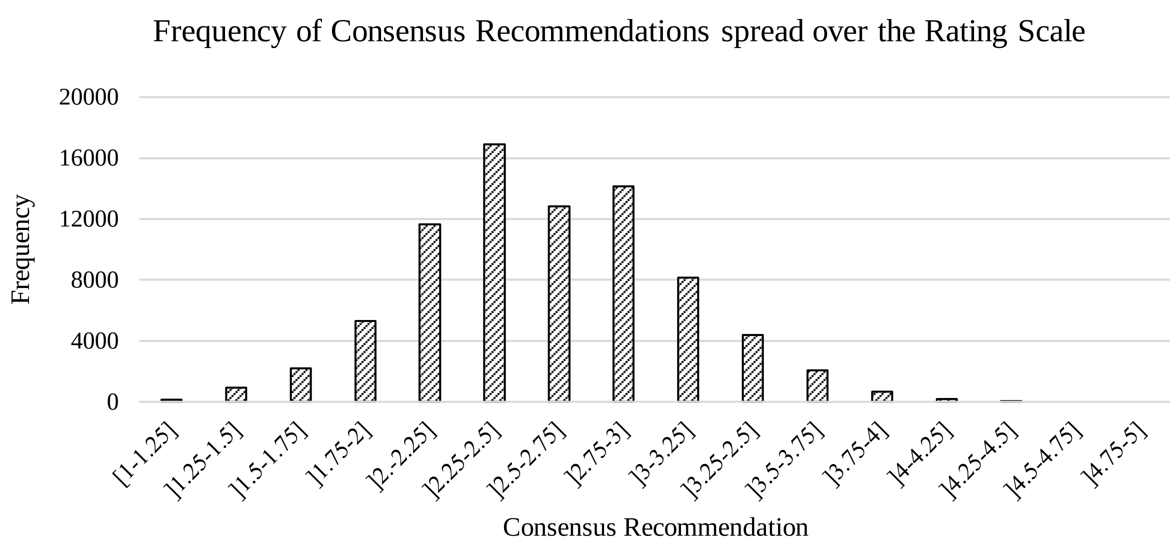
[10] Since 3 stocks are omitted from this study and some stocks didn't trade on some days, there are not continuously 20 stocks to be grouped into the different portfolios, especially during the first year of the sample period. On average there are 19.72 stocks that are sorted into the different portfolios each day.

Table 5

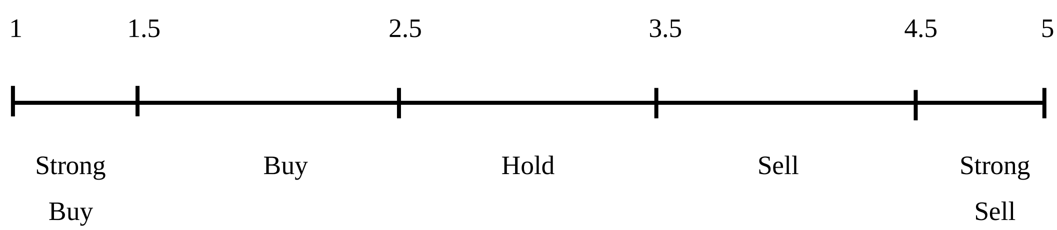
Frequency of Consensus Recommendations and Number of Stocks per Portfolio

Table 5 is divided into different sections; in the first section we can see the frequency of analysts' consensus recommendations spread over the rating scale. In the rows below the graph, the cut-offs of the methodology used by Barber et al. and the average ratings of the quintiles of the methodology used in this paper are visualized to help understand what stocks are attributed to which portfolio. The second section lists the average number of daily observations within each portfolio of the two sets of portfolios.

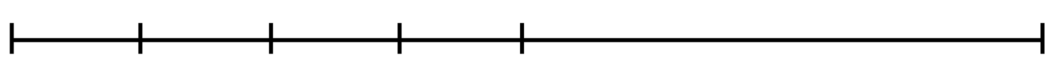
First Section



Rating Scale



Brackets Barber et al.



Sorted into Quartiles

*The circles show the average rating in each portfolio

Second Section

Average number of daily observations	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5
Barber et al. (2001)	0.26	1.9	7.1	6.7	3.8
Quartiles (4 Portfolios)	4.88	5.21	4.84	4.79	-

Table 6 provides additional descriptive statistics of the different portfolios supplemented with data relative to the BEL20 index.

In the first column the average number of firms within each portfolio is displayed and indicates that the mean is spread relatively uniformly between 4.8 and 5.2. As stated earlier, the second portfolio contains slightly more stocks on average than the other portfolios, however, that does not alter future results.

In the next column each portfolios' part of the total market capitalization is displayed. When observing these numbers, we can see that the majority is contained in portfolio 1 and 2 and only a small part is comprised within the last two portfolios meaning that the favorably recommended stocks are large capitalized firms (compared to the other companies in this study, not all of them should, however, be considered as large capitalized firms per se) and the less favorably recommended ones are rather small capitalized firms. As a matter of fact, more than 75 precent of the total market capitalization are comprised in the first 2 portfolios. This is consistent with Barber et al. (2001) who attributed this observation to the conventional wisdom that analysts are reluctant to issue negative recommendations on large firms in order to maintain good relationships with them and secure future possible investment banking business.

When investigating the average analysts' consensus recommendation of each quartile, the high concentration of the consensus rating between 2 and 3 is exposed again. The means of the portfolios are all very close to each other and the mean absolute deviation shows that the 2 middle portfolios are not dispersed at all. Only portfolios 1 and 4 show higher values of dispersion since they have to include the extreme values at both ends of the rating scale.

In light of this study, the column showing the mean monthly return figures of each portfolio is obviously the most interesting. As one would expect, the monthly returns are monotonically decreasing while moving from the first portfolio to the last. The first quartile, representing the most favorably recommended stocks, yields a monthly raw return of 0.65 percent, which is however not significantly different from 0 at a confidence level of 5 percent (with a t-statistic of 1.495). The second portfolio yields a considerably lower raw return of 0.56 percent per month, which is again not statistically different from 0. The third portfolio containing the 3 quartiles of most recommended stocks earn a monthly return of 0.09 percent on average and against intuition and what previous literature has shown, the last portfolio doesn't yield a significantly negative monthly return, since it is very close to a return of zero on average. This monotonic decrease in returns, while moving from the most to the least recommended portfolio, suggests that analysts do convey important value to investors. This is especially the case for positive recommendations, but not necessarily true for least recommended stocks since they do not obtain negative returns. This could, however, be tied to the fact that analysts are reluctant to issue sell recommendations and as shown earlier, the average consensus recommendation of the last quartile (3.23) is still in the range of a Hold recommendation. Since these portfolios are based on analysts' consensus recommendations a certain number of transactions have to be carried out each month in order to build them, which will impact the net returns of the investor which decides to replicate one of the portfolios. Using the method which divides the stocks into quartiles sorted from best to worst recommendation reduces the transaction insensitivity compared to a model with fixed brackets. Thus, the average number of transactions executed per month is fairly low ranging from 1.2 to 3.7 transactions per month. Consequently, the net returns would not be impacted that much from excessive transaction costs.

The last section of table 6 gives an overview of a portfolio containing all constituents of the BEL20. The mean consensus recommendation is 2.60, which corresponds to a split between a Hold and a Buy rating and the associated monthly return is 0.19 percent. This suggests that the first portfolio is able to outperform the index, the second earns a similar return and the last two portfolios perform worse than the index.

Table 6

Descriptive Characteristics for Portfolios Formed based on Analysts' Consensus Recommendations, from 2005 to 2020

The following table gives an overview of descriptive characteristics of the different portfolios formed on the basis of analysts' consensus recommendations from January 2005 until September 2020. The studied characteristics are; the daily average number of firms in each portfolio, the percentage of the total market capitalization contained in each of the portfolios on average, the average rating of each portfolio, the dispersion of the analysts' consensus recommendation within each portfolio, the monthly return of each portfolio and the average number of transactions per month that had to be carried out to build each portfolio. The measure used for dispersion within a portfolio is the mean absolute deviation (MAD), which is the average distance between each data point and the mean of the sample. It gives us an idea about the variability in each portfolio.

Portfolio	Avg. Number of Firms	% of Total Market Cap	Average Cons. Rating	Dispersion of the Cons. Rec. (MAD)	Average Monthly Return (%)	Average Transactions per month
1 (most favorable)	4.88	37%	2.04	0.15	0.65%	1.65
2	5.21	39%	2.41	0.08	0.21%	3.07
3	4.84	13%	2.76	0.10	0.09%	2.70
4 (least favorable)	4.79	11%	3.23	0.19	0.00%	1.20
BEL 20	20.00	100%	2.60	0.39	0.19%	-

Table 7 provides the coefficient estimates for the Four-Factor Model time series regression representative of the three models since this model is the most complete and contains all factors present in the CAPM and in the Fama & French regression. The raw returns and the model's intercepts are also displayed in order to detect how well the model is able to explain the raw returns by the help of the different factors it uses.

When observing the coefficient estimates of the market risk factor one can see that the first one moves in a similar fashion as the market and shares the market's volatility. The other portfolios, however are theoretically less volatile than the market with coefficients below one. If risk would be considered as volatility, one could say that the first portfolio is the riskiest and that the last one is the least risky. Of interest, when inspecting the other coefficients of the Four Factor model, is the fact that only some of them are statistically significant from zero. At a 1 percent confidence level, the only significant coefficients are SMB and WML for portfolio 2. At a 5 percent confidence level, the SMB factor is significant for portfolio 1 as well as WML is for portfolio 4. In our case, this means that portfolios 1 and 2 are composed of smaller firms. This finding is surprising considering that the descriptive statistics showed that first 2 portfolios were composed of companies with larger capitalization than the last 2 portfolios. But as already mentioned this could be due to the fact that the Belgian index is composed of smaller capitalized firms than some other bigger European Indices. Nevertheless, as shown by previous literature recommendations on smaller companies tend to be more influential, which seems to be accurate in our case since the first 2 quartiles clearly outperformed the market.

Table 7

Coefficient Estimates for the Four-Factor Model, from 2005 to 2020

The following tables specifies the coefficient estimates of the Four-Factor model, as an indication for all other models containing some of those factors represented in the Four-Factor Model. The coefficient estimates are obtained from a time-series regression of the portfolio excess returns ($R_p - Rf$) on the market excess return ($R_m - Rf$), a zero-investment size portfolio (SMB), a zero-investment book-to-market portfolio (HML), and a zero-investment momentum portfolio (WML). The t-statistics are listed below the coefficient estimated and each of them relates to the null hypothesis that the associated coefficient is equal to zero. The values with a t-statistic significant at a 1%, 5% or 10% percent level are marked with ***, ** or * respectively.

Portfolio	Raw Returns (%)	Coefficient estimates for the Four-Factor Model: ($R_m - Rf$)	SMB	HML	WML	Alpha of the 4 Factor Model
1 (most favorable)	0.65	1.00	0.32**	0.00	–0.07	0.52*
	(1.495)		(2.200)	(0.027)	(–0.824)	(1.895)
2	0.21	0.89	0.35***	–0.11	–0.38***	0.33
	(0.506)		(2.689)	(–0.948)	(–4.824)	(1.340)
3	0.09	0.75	0.31*	–0.01	–0.12	–0.01
	(0.218)		(1.812)	(–0.072)	(–1.091)	(–0.046)
4 (least favorable)	0.00	0.51	0.11	0.16	–0.16**	–0.01
	(–0.012)		(0.854)	(1.333)	(–2.009)	(–0.031)

The last portfolio shows a significant negative coefficient for the WML factor, indicating that the portfolio is to some extend composed of past “looser” stocks, which seems to be intuitive since the stocks in this portfolio have received the lowest consensus recommendations. However, the negative WML coefficient for the second portfolio seems to be counterintuitive since the stocks in this portfolio have received rather favorable recommendations. If we observe the difference between the raw return and the models’ alpha, we can see that the model is not able to explain the raw returns of the second portfolio, on the contrary, the model shows even higher abnormal raw returns. In the case of the other portfolios the model is able to explain the raw returns to some extent since the alphas are lower in every case, however, the only significant alpha is the one of the first portfolio.

4.3 Observed Returns

As stated in the previous section, the monthly raw returns of the different portfolios are monotonically decreasing when moving from the most favorable to the least favorable portfolio. Table 8 documents the different returns after accounting for several factors. This will ultimately give us an idea of the abnormal returns and if profitable investment strategies exist when following analysts’ consensuses recommendations.

The first 2 columns indicate that the most favorably recommended stocks achieve positive monthly returns on average over the 189 months. Investing in the first portfolio could yield monthly raw returns of 0.65 percent with a t-statistic of 1.495, which makes it not statistically different from zero at a 10 percent confidence level. The three less favorably recommended portfolios yield monthly raw returns that are positive but not statistically different from 0 at a 10 percent confidence level. Obviously, the market adjusted returns are lower than the observed raw returns showing a deterioration of approximately 0.15 percent per month. Hence, one could assume that an investor could benefit from analysts’ consensus recommendations by investing in the most favorably recommended Belgian stocks and outperforming the respective market by 0.5 percent on a monthly basis (disregarding transactions costs) with a t-statistic of 1.880, which translates to a yearly return of 6.17 percent. The market-adjusted return of the next most favorable quartile is still positive but not significantly different from zero. The two less favorably recommended quartiles underperform

the market, showing negative market-adjusted returns, hence making them less desired than detaining the market portfolio.
When analyzing the intercepts, which represent each model's alpha, we can see that those of the quite simplistic CAPM model are lower than raw returns, indicating that this model is able to explain abnormal returns to some extend with only the market-risk premium at hand. The abnormal returns of this model show a deterioration of the abnormal returns when the consensus worsens, which suggests that the better the recommendation the better the abnormal returns. In this case, the abnormal returns of the least favorably recommended stocks are even negative with an alpha of –0.17 percent, that is not significantly different from 0.

The following models have more factors at hand to explain the raw returns and one would expect, that the alphas would be further offset by the market-risk, size, book-to-market or price momentum factors. After having applied those regression models, the abnormal returns are only inferior to those of the CAPM in some cases, meaning that the chosen factors were able to explain the raw returns to a further extent but not for every portfolio. Applying all those models to the first portfolio yields a positive monthly abnormal return between 0.47 and 0.52 (with a t-statistic of 1.748 and 1.895, making them statistically significant at a 5 percent confidence level, but they are statistically different from zero at a 10 percent confidence level) for the Fama and French and the Four Factor model respectively. This means that the first portfolio generates on average a monthly abnormal return of 0.47 to 0.52 percent, which translates to an abnormal annual return between 5.79 and 6.42 percent. The abnormal returns of the second portfolio are not significantly different from zero for both models. Similarly, the alpha values for the last 2 quartiles are not significant.

These abnormal returns indicate that there is an interest in buying stocks of the first portfolio, which contains the most favorably recommended quartile of stocks. However, there seems to be no interest in buying the second portfolio when considering abnormal returns. But short selling the stocks contained in last portfolio does yield some abnormal return, that is however not significantly different from 0.

Lastly, as stated in Barber et al. (2001) a strategy that invests in the most favorably recommend stocks on a daily basis would be transaction intensive and some part of returns would be offset by the associated transaction costs.

Table 8

Percentage Monthly Returns Earned by Portfolios based on Analysts' Consensus Recommendations, from 2005-2020

The following table presents the monthly returns earned by portfolios built according to analysts' consensus recommendations. Raw returns are average returns yielded by each portfolio per month. Market-adjusted returns are the averages of the difference between the raw returns and market returns (Return of the Bel All Shares index). The intercept of the CAPM model is the estimated intercept of a time-series regression of the portfolio's excess return (R_p – Rf) on the market excess return (R_m – Rf). The Fama & French intercept is the estimated intercept of a time series time-series regression of the portfolio excess return (R_p – Rf) on the market excess return (R_m – Rf), a zero-investment size portfolio (SMB), and a zero-investment book-to-market portfolio (HML). The intercept of the Four-Factor Model is the estimated intercept of the Fama & French regression to which has been added a last independent variable that is a zero-investment momentum portfolio (WML). The t-statistics are listed below the intercept estimates and each of them relates to the null hypothesis, that the associated return or intercept is equal to zero. The values with a t-statistic significant at a 1%, 5% or 10% percent level are marked with ***, ** or * respectively.

Portfolio	Mean Raw Return (%)	Mean Market-adjusted return (%)	Intercept from CAPM	Fama & French	Four-Factor
1 (most favorable)	0.65	0.50*	0.50*	0.47*	0.52*
	(1.495)	(1.880)	(1.879)	(1.748)	(1.895)
2	0.21	0.06	0.06	0.04	0.33
	(0.506)	(0.242)	(0.239)	(0.151)	(1.340)
3	0.09	–0.06	–0.07	–0.10	-0.01
	(0.218)	(–0.190)	(–0.225)	(–0.324)	(–0.046)
4 (least favorable)	0.00	–0.15	–0.17	–0.13	–0.01
	(–0.012)	(–0.555)	(–0.708)	(–0.537)	(–0.031)

4.4 Investment strategies

As discussed above, these results could be a motivation for investors to invest in securities that have been most favorably recommended by analysts. Nonetheless, I will also assess the strategies that invest in securities that have been favorably recommended by analysts and short-sell those that have received the least favorable consensus recommendations. To test different investment approaches involving the historical components of the Belgian BEL20 index, I built 4 different strategies in order to compare their respective average monthly returns.

Table 9

Comparison of Investment Strategies Based on Analysts' Consensus Recommendations

The following table shows the average monthly returns, the intercept of a Four Factor regression, the Sharpe Ratio, the Treynor Ratio and the Information Ratio of different investment strategies based on analysts' consensus recommendations. The strategies buy or short-sell stocks included in the BEL20 index based on their consensus ratings and are re-balanced on a daily basis. Strategy 1 is long only and invests in stocks of the first portfolio. Strategy 2 buys all stocks within portfolios 1 and 2. Strategy 3 buys the stocks contained in portfolio 1 and short sells those contained in portfolio 4. Lastly, strategy 4 buys all stocks within portfolios 1 and 2 and short sells those being in portfolio 4. The alpha of the Four Factor regression is computed on monthly returns. The Sharpe, Treynor and Information ratios are all annualized. Skewness and Excess Kurtosis are computed on monthly returns. The market returns are represented by the returns of the BEL All Shares Index, which is also the chosen benchmark for the Information ratio. The values with a t-statistic significant at a 1%, 5% or 10% percent level are marked with ***, ** or * respectively.[11]

	Strategy 1	Strategy 2	Strategy 3	Strategy 4
Mean Monthly Return (%)	0.65	0.44	0.33	0.30
Intercept of the Four Factor Regression (alpha)	0.52*	0.43**	0.06	0.16
Standard deviation	5.97	5.37	2.58	2.98
Beta	1.02	1.00	0.21	0.47
Sharpe Ratio	0.26	0.16	0.18	0.12
Treynor Ratio	5.33	2.92	7.56	2.71
Information Ratio	0.47*	0.37	0.14	0.16
Skewness	–0.51	–0.70	0.13	–0.49
Excess Kurtosis	1.16	2.17	0.95	2.33

[11] The t-Test was performed for the mean monthly return, the intercept of the Four Factor Regression the Sharpe ratio and the Information ratio. The mean monthly return was tested to be different from the market return, the alpha was tested to be different from zero, the Sharpe ratio was tested to be different from the Sharpe ratio of the market and the Information ratio was tested to be different from 0.

Strategy 1 is long only and invests in stocks of the first portfolio. Strategy 2 is also long only and invests in portfolios 1 and 2. The third strategy is a long-short strategy and buys the first portfolio and sells short the last one. Lastly, strategy 4 invests in portfolios 1 and 2 and sells short the fourth portfolio. Table 9 gives an overview of some useful metrics to evaluate the different strategies.

Bearing the previously obtained results in mind, it is no surprise that strategy 1 - that is long only in the most favorably recommended stocks - outperforms all other strategies when it comes to average monthly returns (0.65 percent per month, which is however not statistically significant from the market return of 0.15 percent with a t-statistic of 0.908). The second highest average return of 0.44 percent is obtained by the second strategy that is also long only and invests in the first 2 quartiles of most favorably recommended stocks (with a t-statistic of 0.560 this strategy's return is also not statistically different from zero at a 5 percent confidence level). Additionally, when assuming short-selling limitations, these two strategies are also the most feasible. Strategies 3 and 4, which include short selling of the least favorably recommended portfolio, have inferior returns to the first two strategies and yield monthly returns around 0.3 percent on average. This is still higher than the average market return of 0.15 percent. When it comes to the alpha, the first and second strategies outperform the others by far, obtaining abnormal monthly returns of 0.52 percent (which is statistically different from 0 at a confidence level of 10 percent with a t-statistic of 1.895) and 0.43 percent (which is statistically different from 0 at a 5 percent confidence level with a t-statistic of 2.299) for the first and second strategy respectively. These abnormal returns are obtained after accounting for market-risk, size, book-to-market and momentum factors. This means, when only considering return, the first strategy clearly outdoes the others even if the others still remain profitable disregarding transaction costs. Accordingly, an investor following such a strategy would earn an abnormal return of 6.42 percent per year. Nonetheless, the associated risk can't be neglected and the standard deviation indicates that the first strategy shows the highest volatility (with a standard deviation of 5.97) closely followed by the second strategy (with a standard deviation of 5.37). Strategies 3 and 4 show inferior volatility with a standard deviation of monthly returns between 2.5 and 3. To compare these measures to a reference point, the BEL All Shares Index registers a standard deviation of 4.63.

To evaluate the different strategies with a more risk-return oriented approach, different performance ratios are computed. First, the Sharpe ratio (first introduced by Sharpe in 1966) assesses the portfolio's performance based on the total risk of the portfolio. It measures the portfolio's excess return over the risk-free rate (yield on Belgian Government Bond with a maturity of 10 years) in the relation to the overall risk, which is measured by the standard deviation of the monthly returns. The first strategy obtains a Sharpe ratio of 0.26, which would mean that, for any additional unit of risk, the first strategy receives an additional return of 0.26 percent, making it questionable to accept the additional risk undertaken by the investor. In the case of the 3 following strategies one can see that even if the average return of the third strategy is lower than the return of the second it outperforms the second strategy when it comes to risk adjusted returns thanks to a lower volatility. The Sharpe ratio of the market corresponds to a negative value of –0.03 since the risk-free rate is higher than the mean market return. A t-test was performed to assess the significance of the difference between the Sharpe ratios of the strategies and the market portfolio, however, none of the strategies' Sharpe ratios was significantly different from the Sharpe ratio of the market portfolio (at the 1, 5 or 10 percent level). The second risk-adjusted return measure is the Treynor ratio (first introduced by Treynor in 1965), which measures a portfolio's excess return in relation to its systematic risk, represented by the portfolio's beta. Again, the risk, this time measured by the systematic risk, is highest for the first and second strategy with a beta value around 1, meaning the strategies move in a similar fashion as the market and therefore present only little unsystematic risk. Strategies 3 and 4, however, register beta values below 1, meaning they are less volatile than the market and therefore less risky but also less likely to experience higher capital gains. Opposed to the Sharpe ratio, the Treynor ratio is highest for the third portfolio (7.56) thanks to a low beta value. It is followed by the first strategy with a Treynor ratio of 5.33 than the second strategy (2.92) and finally the last strategy (2.71). The last ratio is the Information ratio (Goodwin [1998]), which measures the risk-adjusted market excess return and makes it particularly interesting because it compares the different strategies to the benchmark returns. The Information ratio is computed by dividing the difference of the portfolio return and the market return by the tracking error, which is the standard deviation of this excess return. The fact that we can compare the different investment strategies to their benchmark makes this ratio especially interesting since the strategies are composed of elements included in the benchmark, which is the BEL All Shares index. Additionally, the ratio measures the consistency in generating excess returns measured by the tracking error. In line with previous observations of the Sharpe ratio, the Information ratio is highest for the first strategy with a value of 0.47, followed by the second strategy with a value of 0.37. Of those two, only the first one is significantly different from 0 (at a 10 percent confidence level) with a t-statistic of 1.880. This makes the first strategy more attractive since it creates excess returns more consistently. Consequently, the previous outcomes make the first strategy the best regarding risk-adjusted returns and also regarding absolute returns.

Only the third strategy has a positive skewness, meaning that investors who follow this strategy can expect recurrent small losses and few large returns, which is more desirable than the negative skewness values of the other portfolios. However, an investor could also prefer the negatively skewed strategies arguing that he prefers frequent small wins and a few large losses over frequent small losses and few large gains. Regarding the excess kurtosis, the first and third strategy exhibit the least risk of extreme values since they have the lowest excess Kurtosis. Strategies two and four are more prone to extreme returns on either side.

Table 10 will allow us to assess the periodicity and the impact of recessions on the different investment strategies. Besides, we can compare performances of the different investment strategies to the evolution of the respective market. This will show if the returns are shaped by the economic cycle during the chosen sample period and if some strategies are able to outperform the market.

In the last column we can see that the market experienced major downturns during the financial crisis of 2008, in 2011, 2018 and in 2020 due to the global outbreak of the Covid-19 virus. The table highlights the high volatility of the first and second strategy showing extreme return figure during turbulent economic cycles such as the 2007 to 2009 period. What comes to attention as well is that the first portfolio shows steep rebounds after economic downturns, such as the periods after 2008 and 2018. This suggests that the most favorably recommended stocks are able to better recover from recession periods than less favorably recommended stocks. However, strategies three and four show far more balanced returns especially during financial dips during which they are mostly able to outperform the market (such as in 2008, 2011 and portfolio 3 in 2018). The annualized yearly return figures indicate a decent performance of 5.68 percent for the first portfolio and returns between 3 and 3.6 percent for the other three strategies. Compared to the market these returns seem to be interesting, since during the analyzed period, the Belgian market was neither able to achieve consistent high returns nor show healthy recoveries after recessions. However, the strategies do not include transaction costs, which would alter these results to some extent.

Table 10

Yearly Returns of different investment strategies, 2005-2020

The following table displays the yearly return figures of the different investment strategies that were previously described. The yearly returns were computed by compounding the monthly returns of each portfolio. The last row indicates the annualized return of each investment strategy. The last column serves as a reference and displays the yearly return figures of the BEL All Shares Index, which represents the Belgian stock market.

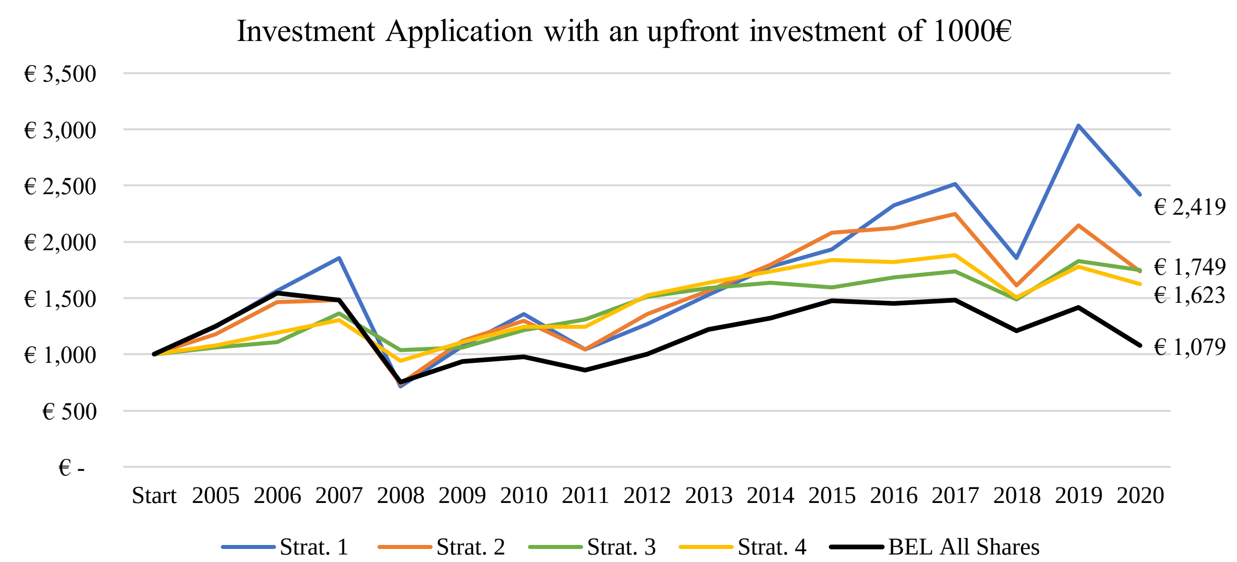
	Strategy 1	Strategy 2	Strategy 3	Strategy 4	BEL All Shares Index
2005	24.7%	17.8%	6.4%	8.1%	25.1%
2006	25.5%	24.4%	4.4%	10.4%	23.5%
2007	18.5%	1.1%	22.7%	9.3%	–4.0%
2008	–61.4%	–50.2%	–23.9%	–27.8%	–49.2%
2009	50.3%	51.8%	2.2%	17.8%	24.6%
2010	26.4%	16.0%	14.8%	12.3%	4.4%
2011	–23.3%	–19.6%	7.8%	0.0%	–12.4%
2012	21.8%	29.9%	15.2%	22.4%	17.0%
2013	20.4%	15.6%	5.1%	7.1%	21.8%
2014	16.4%	14.7%	3.1%	6.5%	8.4%
2015	8.6%	15.7%	–2.4%	5.7%	11.5%
2016	20.4%	1.9%	5.6%	–1.1%	–1.6%
2017	8.1%	6.0%	3.2%	3.4%	2.0%
2018	–26.1%	–28.2%	–14.4%	–20.0%	–18.4%
2019	63.3%	33.1%	22.9%	18.0%	17.0%
2020 (Jan-Sep)	–20.3%	–19.3%	–4.4%	–8.7%	–23.8%
Annualized Yearly Return	5.68%	3.50%	3.56%	3.07%	0.48%

To further illustrate this, an investor that would have invested €1.000 in January 2005 would end up with €2.419 by the end of September 2020. The same amount invested in the second, third and fourth strategy would return €1.735, €1.749 and €1.623 respectively and if invested in the market the investor would end up with €1.079. As a remainder, the return figures do not account for dividends and the same goes for the market index.

Figure 2

Investment Application with an upfront investment of 1,000€

The following figure represents the evolution of different investment applications of the previously constructed strategies. The application consists in investing 1,000€ at the beginning of January 2005 in either strategies 1, 2, 3 or 4. As a reference point the BEL All Shares index is added to the graph representing the Belgian economy.



To sum up, it can be said that the most profitable investment strategy is the first one that is long only in those stocks of the BEL20 Index that have received the highest consensus recommendation. Even with a considerably high volatility the first strategy still outperforms the others on a risk-adjusted basis with the exception of the Treynor ratio, that is highest for the third portfolio benefiting from a low beta.

4.5 The Value of Consensus Recommendations under specific Circumstances

In this subsection the value of analysts' consensus recommendations will be investigated with respect to certain variables. Research has recurrently shown that analyst recommendations are more predictive under certain circumstances. Amongst them is the finding that the impact on smaller firms tends to be greater than the impact on larger capitalized firms but since this study focuses on the 20 largest companies of the Belgian economy, such analysis would make little sense. Secondly, several characteristics of a recommendation itself influence the magnitude of the price changes they induce, such as recommendation revisions that skip a rank or revisions to the extremes, which turn out to have a greater impact on the future stock prices. Additionally, timely access to the release of the new recommendations is very important to maximize the value of this information. But as this paper has only access to the daily consensus of analyst recommendations without individual recommendation information it is impossible to analyze the impact with respect to those variables. In a similar fashion, the proven effect of increased predictive power when accompanied by news or earnings releases and if issued from analysts who benefit from better reputation can't be assessed in this study due to data constraints. Therefore, I will direct my attention to other factors, that may or may not improve analyst recommendation's ability to predict future stock prices. To acknowledge the fact that recommendation changes and especially those which skip a rank are more predictive, I test the predictive power of the change in consensus recommendations. And secondly, I will test whether the consensus is more reliable in periods of high market volatility and low investor sentiment or in the opposite periods.

4.5.1 The Value of Changes in Analysts' Consensus Recommendations

Several researchers found evidence that recommendation revisions are of greater value than the absolute level of new recommendations (e.g., Juergens, [1999] and Jegadeesh et al. [2004]). To assess this claim on the Belgian market, while being limited to the consensus data, I will test whether changes in consensus ratings are more predictive of future returns than their absolute values. To do so, two portfolios are constructed and rebalanced daily with respect to the change in the consensus recommendation of each stock. If a stock is subjected to an increase of more than 0.1 in its consensus recommendation, it will be added to the first portfolio and will be removed from the portfolio after three weeks or earlier if the consensus rating decreases. A second portfolio, which includes stocks with a downgraded consensus rating, is built in an analogous way but with a holding period of three months. The holding periods are fixed based on the findings of Womack (1996) but slightly adapted. In his study Womack detected post-recommendation drifts with a length of 1 month for upgrades and 6 months for downgrades. In the case of this study, the post-recommendation drifts of upgrades are similar, but those of downgrades are shorter and the lowest returns seem to be achieved for a holding period of about 3 months.

Table 11

The Value of Changes in Analysts' Consensus Recommendations

The following table displays some return measures and descriptive statistics of the upgrade and downgrade portfolios with holding period of 3 weeks and 3 months respectively. The values with a t-statistic significant at a 1%, 5% or 10% percent level are marked with ***, ** or * respectively.

	Average monthly Return	Sharpe Ratio	Average Transactions per month
Portfolio 1 (upgrades)	0.66%	0.29	4.77
Portfolio 2 (downgrades)	0.04%	–0.10	3.57

The findings show evidence of predictive power for upgrades but this is not the case for downgrades. The first portfolio yields an average monthly raw return of 0.66 percent and the second portfolio of 0.04 percent. None of them are however statistically different (with t-statistics of 0.962 and –0.227 respectively) from the market returns (0.15 percent per month). One can see that the first portfolio outperforms the market, even if not statistically significant by 0.51 percent per month and the second portfolio underperforms the market but does not yield negative returns as one would expect. On an annualized basis, the first portfolio would yield 6.15 percent per year, whereas the portfolio, which invests in the quartile of stocks that received the most favorable consensus recommendation earns 5.68 precent per year. Similarly, the risk-adjusted return analysis of the Sharpe ratio slightly favors the recommendation changes over the absolute values (0.29 for the portfolio investing in positive changes and 0.26 for the first portfolio focusing on absolute consensus ratings, none of them are statistically different from the market's Sharpe ratio). These findings seem to indicate that an increase of the analysts' consensus recommendation is marginally more predictive of future returns than its absolute value, however, the difference is minimal. Yet, downgrades are however not able to predict future stock price decreases. A strategy that would buys the upgrades and short-sells the downgrades with holding periods of three weeks and three months respectively generates an average monthly return of 0.27 percent, which translates to an annualized yearly return of 2.66 percent.

4.5.2 The Value of Consensus Recommendations with respect to market volatility

In this subsection I will test whether the value of analysts' consensus recommendations is impacted by investor sentiment. Investor sentiment is commonly represented by the investors' market volatility expectation as captured by the implied volatility index (hereafter mentioned as VIX).[12] The VIX was first introduced by Whaley in 1993 and launched by the Chicago Board Options Exchange in the same year. Since then, the index is widely followed as an implied measure of expected future volatility and is also known as the investors' 'fear index'. A study by Kliger and Kudryavtsev (2013) investigates the relationship between investors' market volatility expectations and abnormal returns around recommendation revisions. The researchers find that positive excess returns after recommendation upgrades are of greater magnitude when the VIX decreases and negative excess returns following downgrades are larger when the VIX increases. Firstly, they take a rational explanation for this effect by concluding that the VIX serves as an indicator of future economic conditions but they also attribute these effects to investors' moods. The researchers suggest that investors' sentiment, which is represented by the VIX, influences their reaction to stock recommendation revisions. Consequently, investors in good mood (VIX decreases) are more likely to put faith in upgrades and react more strongly to positive recommendation changes. Equivalently, investors in bad mood are more likely to perceive a negative financial outcome as more plausible and therefore they will react more intensely to negative recommendation changes. To test whether their findings remain accurate under the circumstances of the Belgian market, I will compare the previously built portfolios and strategies with respect to investors' sentiments. To put this to the test I stick to the methodology previously developed, which divides the stocks into quartiles based on their consensus rating but it will be influenced by the daily VIX values. As an indicator for high or low volatility I chose to use the VIX reference value of 20. This is an approximation made by Edwards and Preston (2017) in their paper "A Practitioner's Guide to Reading VIX" in which they assumed a VIX level over 20 to be high and indicate excessive future volatility. Subsequently, I test the different portfolios under two different scenarios, in the first scenario, the stock is added to the respective portfolio if the VIX value at the previous close is below 20 (representative of high investor sentiment and low implied future volatility) and the

[12] The Euro Stoxx 50 Volatility Index which is the European equivalent for the VIX was tested as well in light of this study, but due to similar results and the wider use and acceptance of its U.S. counterpart, the U.S. VIX measure was chosen for this study.

portfolio stays in the money if it's above. In the second scenario, the stocks are added to the respective portfolios if the VIX value of the previous trading day closed above 20 (representative of low investor sentiment and high implied future volatility) and stays in the money if below. These portfolios are then compared to the ones build in the basic scenario not taking into account the evolution of the VIX (as stated under the section *Research Methodology*).

The results indicate a similar outcome to the one obtained by Kliger and Kudryavtsev (2013), indeed, the returns of the most favorably recommended stocks is higher during periods of good investors' mood and the returns of the least favorably recommended stocks are lower during periods of bad investors' sentiment. The first portfolio yields an average monthly raw return of 0.97 percent in scenario one (only invest if VIX of previous close is lower than 20) compared to a return of 0.65 percent per month in the basic scenario. The monthly returns of portfolio 1 under scenario one are however not significantly different from those of portfolio 1 under the basic scenario with a t-statistic of 0.248. Similarly, the returns of the last portfolio containing the least favorably recommended stock are lower under scenario two (only invest if VIX of previous close is higher than 20) than they are under the basic scenario. Hence, a strategy that invests in the most favorably recommended quartile of stocks in periods of good investors' mood and short-sells the least favorably recommended quartile of stocks in periods of bad investors mood should outperform the strategy 3 developed under the basic scenario in the subsection *Investment Strategies* (as a reminder strategy 3 buys the first quartile and short-sells the last quartile without considering VIX values). And indeed, the long-short strategy which accounts for VIX values outperforms the strategy not considering investors' sentiment (the difference is however not statistically significant with a t-statistic of 1.325. On an annualized basis, the strategy accounting for investors' mood yields 9.44 percent whereas the same strategy not accounting for investors' mood only yields 3.61 percent per year. Nevertheless, one should consider that the strategies including investors mood into their construction have a higher number of transactions as indicated in the last column of Table 12.

Table 12

Comparison of portfolios and strategies based on analysts' consensus recommendations with respect to investors' sentiment measured by the VIX

The following table compares similar built portfolios under different scenarios. Without further specification the portfolios are built as stated under the section *Research Methodology*, if an addition is made concerning the VIX, the portfolio only includes the stocks of the given quartile (portfolio 1 invests in the first quartile, containing stocks receiving the best recommendations, portfolio 2 in the second quartile and so on) if the VIX of the previous closing date satisfies the mentioned condition. The last two rows display the measures of different investment strategies. The first two columns indicate the average monthly return of the different portfolios/strategies and the t-Statistic that assesses whether or not the average monthly returns are statistically different from each other. The third column displays the annualized yearly returns and the last column specifies the Sharpe ratios for the two investment strategies that are not significantly different of the Sharpe ratio of the Market (–0.03).

	Avg monthly Return	t-Statistic of their difference	Annualized Return	Sharpe Ratio	Average Transactions per month
Portfolio 1	0.65%	0.248	5.77%	-	1.65
Portfolio 1 if VIX < 20	0.97%		8.78%	-	5.78
Portfolio 4	0.00%	–0.477	–1.16%	-	1.20
Portfolio 4 if VIX > 20	–0.39%		–3.04%	-	4.90
Long Portfolio 1 Short Portfolio 4	0.33%	1.325	3.61%	0.18	2.85
Long portfolio 1 if VIX < 20 Short portfolio 4 if VIX > 20	0.89%		9.44%	0.46	10.68

Table 12 gives an overview of the different return figures, comparing strategies controlling for VIX values to the previously built strategies that did not account for measure. The results indicate a strong performance of the portfolios accounting for future implied volatility, both for positive (negative) recommendations paired with good (bad) investors' mood and for the strategy combining both portfolios. This supports the findings of Kliger and Kudryavtsev (2013) with data on the Belgian market and suggests that positive recommendations are more valuable under normal, less volatile market conditions and negative recommendations are more likely to be accurate under turbulent market conditions with low investor sentiment. As pointed out by the researchers these results could be explained by the VIX serving as an indicator of future economic conditions. But it could also be that investors rather trust good reviews in "good" times and put more trust in bad reviews when there is more uncertainty in the markets.

5 Summary and Conclusion

The main objective of this research paper has been to assess the question whether the analysts' consensus recommendations on the stocks figuring in the BEL20 index provide any value to investors. To do so the stocks have been divided each day into quartiles based on their consensus ratings. To evaluate the performance, different return measures such as raw returns, market-adjusted returns and abnormal returns have been computed or estimated. The results indicate that the analysts' expertise is valuable and presents information for investors. The most recommended stocks earn the highest returns and they decrease monotonically when the rating worsens. The last quartile earns the lowest returns but they are not negative as one would expect. This suggests that the least recommended stocks to not necessarily yield negative returns. The raw returns of the first quartile stand at 0.65 percent per month and the last quartile earns an average of 0 percent, however none of them were significantly different from 0. Obviously, this study is not representative of the whole Belgian market since it only contains the 20 largest companies and therefore these results have to be assessed carefully. When considering abnormal returns the most recommended stocks yield a significant 0.50 percent per month and the least favorably recommended stocks earn –0.17 percent per month on average, both under the CAPM model. This indicates that when considering abnormal returns, analysts' consensus recommendations present valuable information for investors, guiding them in the right direction.

As mentioned, this absence of negative returns for the least favorably recommended quartile of stocks seems surprising but it could be due to the fact that this study analyzes only the 20 largest companies of the Belgian economy.

The investment strategies built based on the previously obtained results show interesting results; the most profitable investment strategy is the one with the highest risk that only invests in the most recommended stocks. This strategy earns an annualized return 5.68 percent and outperforms the other strategies even on a risk-adjusted basis with a Sharp ratio of 0.26. Second best risk-adjusted strategy is a long-short strategy that buys the most recommended stocks and short sells the least recommended stocks. This strategy has a Sharpe ratio of 0.18 and an annualized return of 3.07 percent. The mean monthly return of this long-short strategy is 0.33 percent which seems to be quite low compared to the value of 0.90 percent that was obtained by Azevedo and Müller (2020) who constructed a similar strategy that buys the first quintile and sells short the last quintile. But their study was conducted on a larger sample including a multiple of the number of stocks used in this study and they analyzed a much larger sample period of 25 years. Besides these differences the findings still go in the same direction and support the claim that analysts provide value to investors when disseminating recommendations on Belgian companies.

Even if transaction costs would deteriorate these return figures, this study shows that a replication of the constructed portfolios or strategies does not require a large number of transactions. As an example, the long-short strategy that buys the first quartile and sells-short the last quartile registers only an average of 2.85 transactions per month. An interesting addition to this study would be to investigate the impact of transaction costs on such investment strategies. But even if these costs would significantly decrease returns, analysts would still be able to provide guidance for investors since their opinions are directed in the right direction.

Taking these results into consideration, it seems that the markets are not efficient and that the semi-strong hypothesis, stating that investors are not able to profit from publicly available information such as analyst recommendations, ought to be rejected. The evidence of this research suggests that market inefficiencies exist and that positive returns following favorable consensus recommendations exist, but the question whether or not they are exploitable by investors, net of transaction costs, remains uncertain.

Against to what previous literature has documented, changes of consensus recommendations only present minimal added information to the simple absolute value of recommendations. However, this study did not account for individual recommendations and therefore the changes in recommendations were only measured on the consensus value. It would be of interest to further investigate this by analyzing individual recommendations and their revisions.

Interestingly, investors' mood is able to amplify the value of analysts' consensus recommendations and a strategy that invests in the most recommended quartile in periods of good investors' mood and sells short the least recommended quartile in periods of bad investors' mood is able to outperform a similar strategy not taking into account investors' mood. The strategy considering the implied future volatility level for its construction was able to earn an annualized return of 9.44 percent.

Last, this thesis presents some limitations; firstly, I only focused on consensus recommendations and did not focus on individual analysts' recommendations; secondly, I exclusively focused my attention on large capitalized Belgian stocks and not on a broader stock basket; and thirdly I observed gross returns and did not account for transaction costs. Hence, I suggest to investigate the subject in different European stock markets since there in not much research focusing on markets outside of the U.S. As an example, a study focusing on the German, French and Belgian market could be interesting to study the value within analysts' recommendations in central Europe. Additionally, it could be of interest to find a correct approximation for transaction costs and examine their influence on the return figures.

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Executive Summary

Brokerage firms and investment banks spend large amounts of their income on security analysts whose function it is amongst others to review securities and issue recommendations. These security analysts serve as an intermediate between publicly-listed companies and the general public. They can issue negative, neutral or positive recommendations based on their analysis of a particular stock. These recommendations take the form of Sell, Buy and Hold Recommendations and are complemented by research reports on the given company. The professionals publishing these recommendations are deemed specialists in a specific industry and are in a position to review companies adequately. Consequently, an investor could expect to be able to generate excess returns by following the expert's recommendations, but this very matter has been at the center of debates for nearly a century.

Starting as early as 1933, Cowles first found evidence that most stock analysts weren't able to predict future stock price movements. In the past, however, researchers found solid investment value behind these recommendations which is impacted by many factors such as transaction costs, the holding period and the adopted investment strategy. Thus, these findings contradict the strong and semi-strong market efficiency theory stating that investors should not be able to generate excess returns by incorporating information that has already been disseminated to the marketplace, such as an analyst's recommendations which is basically an analysis of existing information.

Since 1933 many researchers have studied the investment value of recommendations and their consensus. Besides, factors making recommendations influential have been investigated, as well as different characteristics of recommendations that amplify their value. The vast majority of these studies focus on U.S. companies and only few have pointed their attention to European stocks or an isolated market outside of the U.S. The core target of this master thesis entitled: "Do Analysts' Consensus Recommendations Have Investment Value: A Study conducted on the 20 Stocks Included in the BEL20 Index", is to assess whether or not analysts' consensus recommendations present any investment value to investors. The sample includes the stocks that made up the index during the sample period starting in January 2005 and ending in September 2020.

The methodology used in the empirical research of this study is similar to the one developed by Barber et al. (2001). Each day, the stocks were sorted into four portfolios based on the analysts' consensus recommendation of the previous close. Portfolio 1 comprises the quartile of stocks with the best recommendations and the last portfolio comprises the stocks allocated into the last quartile. Once each stock was allocated to a specific portfolio, the monthly return figures have been calculated. To account for different factors such as market-risk, size, book-to-market and momentum, I employed three different time-series regressions to compute abnormal return figures. The models used were the CAPM Framework, Fama & French model, and the Carhart 4 Factor model.

The results of the analysis show that the average consensus recommendation is positive and lays between a buy and a hold recommendation. Besides, one can observe that there seems to be a delay in recommendations with respect to the overall performance of the economy meaning that the recommendations are being downward revised after major economic downturns.

When observing the raw return figures, we can see that the first quartile earns the highest returns and the last quartile the lowest returns. This monotonic decrease while moving from quartile one the quartile four supports the claim that analysts do present valuable information for investors. The first portfolio earns an average of 0.65 percent per month and an abnormal return of 0.50 percent under the theoretical framework of the CAPM model. The last portfolio earns an average of 0 percent per month and an abnormal return of –0.17 percent per month. This means that the value within positive recommendations is greater than the value of negative recommendations when considering raw returns. This claim should be taken very carefully since this study only considers the 20 largest stocks and is not representative of the whole Belgian market.

Later on, these findings were used to build and test investment strategies based on the portfolios previously constructed. The findings show that a strategy which is long only and buys the stocks contained in the first quartile earns the highest return and the highest risk-adjusted returns. The Sharpe ratio of such a strategy is 0.26 for the analyzed sample period. The second highest Sharpe ratio of 0.18 was achieved by a long short strategy that buys the stocks of the first quartile and sells short those of the last quartile. This long-short strategy earns a monthly mean return of 0.33 percent.

Additionally, I analyzed the value of changes in analysts' consensus recommendations which turns out to be indifferent to the value of absolute recommendation levels. Another finding of this study is that investors' sentiment is able to amplify positive (negative) recommendations during periods of high (low) investors sentiment, where investors' sentiment is represented by the evolution if the VIX index.

Taking all these findings into consideration, one could conclude that analysts' consensus recommendations present value for investors and are able to guide them into the right direction.