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Analyst Recommendations: Do strong buy recommendations add value?

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Abstract

In this research, the value of strong-buy analyst recommendations is thoroughly examined across ten different countries. Statistical tests and regressions were implemented, showing that long-only portfolio strategies based on strong-buy analyst recommendations lead to statistically significant excess returns in Australia, Germany and South Africa. However, due to analysts' overconfidence bias in the other countries studied, positive excess return cannot be achieved. Contrary to previous studies, only strong-buy analyst recommendations were used, and minimum transaction costs were appropriately accounted to calculate investors' excess return from following strong-buy analyst recommendations.

Key Words

Analyst recommendation, Abnormal Returns, International Market, Excess Return, Overconfidence Bias.

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1. Introduction

Intrigued by the lack of benchmark indices that track the performance of analyst recommendations, this study aimed to research the value creation of analyst recommendations across ten different countries. Although academia has not reached a common conclusion, there has been a lot of research on whether strategies that follow analyst recommendations provide excess return. This is perhaps due to the broadness of the term “following analyst recommendations”. These professionals issue the well-known ex-ante ‘strong buy’, ‘buy’, ‘hold’, ‘sell’ and ‘strong sell’ recommendations. However, there are many ways investors can incorporate these recommendations into their trading strategies. Unlike the existing research which focuses on long-short strategies based on ‘buy’ and ‘sell’ recommendations, this study investigates the effectiveness of long-only trading strategies solely focused on ‘strong buy’ recommendations in ten different countries, in which five of them are developed nations and the other five are developing nations. For each country, the sample stocks analyzed were taken from one of their most liquid indices. The excess return, also known as alpha, was calculated by implementing the Capital Asset Pricing Model (CAPM), the Fama French Three Factor Model, and the Fama French Five Factor Model.¹ The study finds that in Australia, Germany and South Africa, countries in which analysts recommend a balanced ratio among buy and sell suggestions, a statistically significant alpha was generated. However, for the remaining countries, in which sell recommendations represent a small fraction of the total recommendations, the excess return was either negative or not statistically significant. It was, therefore, concluded that the accuracy of analysts' suggestions is impacted by their behavioral biases, especially their overconfidence.

Investors are constantly trying to beat the market through a myriad of different strategies. Although some people might have the experience, knowledge, and time to properly

¹ Momentum factor was added to both Three Factor and Five Factor models.

analyze securities, many investors lack at least one of these factors and, thus, rely on analyst recommendations to achieve their desired level of return. Sell-side analysts issue the so-called ‘blanket recommendations’, which are stock recommendations that are not directed at any specific strategy, but rather to the public as a whole. Unlike the recommendations of sell-side analysts, the research produced by buy-side professionals is usually not available to the public or are released after the fund has already taken a position in the securities. Therefore, the research provided by buy-side analysts have not been included in this paper.

Sell-side analysts work for brokerage houses and investment banks which profit from the sales of securities. Therefore, many critics argued that sell-side analysts were pressured to recommend securities that were advantageous to the business of the companies that they work for. Indeed, before the scandals of Enron, Tyco, and other large companies, analysts were recommending securities of firms in which their prospects were clearly eroding. Therefore, the Sarbanes Oxley Act of 2002 was implemented, imposing regulations to ensure a certain level of independence between sell-side analysts and the companies that they research. Thus, many banks created the so-called Chinese wall in order to prevent conflicts of interest among different departments.² This study, therefore, focused on a time period that started after the implementation of the Sarbanes Oxley Act of 2002.

Founded in 1981, Bloomberg is one of the main providers of financial market information in the world. Since 1973, the Bloomberg Barclays indices has been the most popular indices for fixed income investors looking for unbiased, regulated and representative benchmarks to gauge the risk and returns of an asset class. In 2016, the company bought these assets from Barclays and has been providing its clients with the latest performance data for global and multi-asset class family of indices. These indices allow investors to analyze periodic

² <https://www.sec.gov/news/speech/spch012803cag.htm>

returns and statistical data to make informed investment decisions based on their level of risk.³ Although Bloomberg has expanded its offering of indices, there are no indices that track the performance of analyst recommendations.

Analyst recommendations are issued ex-ante and are not discovered using data mining methods after the returns have been calculated. Therefore, analyst suggestions make a fascinating area of research. This paper aims to examine whether investors can rely on the strong buy recommendations of sell-side analysts and therefore use them to passively achieve excess returns or simply as a measure to reliably compare their own performance.

2. Literature Review

2.1. Efficient Market Hypothesis

Before diving into this study, it is crucial to understand the three forms of the efficient market hypotheses (EMH) developed independently by Fama (1963) and Samuelson (1965). According to this theory, markets consider all relevant information when determining share prices, thus beating the market is only achievable by purchasing higher risk investments. The weak form asserts that technical analysis is useless in assisting investors in their trading decision as current stock prices accurately represent all historical data. The semi-strong hypothesis goes beyond technical analysis and states that fundamental analysis cannot aid investors either, as security prices adjust rapidly to the release of public information as well. The strong form asserts that not only public information is reflected in share prices, but also private information. Therefore, any type of information cannot give investors a competitive edge.

This paper focuses on questioning the semi-strong form by studying whether consistent alpha could be generated over the long run across different international markets.

³ <https://www.bloomberg.com/professional/product/indices/>

2.2. The Random Walk Theory

Jules Regnault (1863) introduced the random walk hypothesis concept in its earliest form. According to this theory, stock price fluctuations have the same distribution and are unrelated to one another. As a result, it is presumptive that a stock price or market's historical trend cannot be utilized to forecast its future course. In essence, the random walk theory asserts that stocks follow a random and unpredictable course, rendering all stock price prediction techniques ultimately useless.

Malkiel (1973) went further and concluded that: “A blindfolded monkey throwing darts at a newspaper’s financial pages could select a portfolio that would do just as well as one carefully selected by experts”. Therefore, the random walk hypothesis is widely used as a persuasive justification for the Efficient Market Hypothesis legitimacy.

2.3. Value Destruction of Analyst recommendations

Alfred Cowles (1993) pioneered the studies of achieving abnormal stock returns by following stock recommendations. The author concluded that investors could not earn excess return by following sell-side analysts during the years of 1928 and 1932. In fact, according to his research, investors earned -1.43 percent excess return.

Bradshaw (2011) stated that security analysts multi-task and deal with conflicts of interest, which results in overly optimistic and ineffective forecasts. The author suggested that there is not much evidence supporting their methodology either.

In a more recent study, Guo, Li and Wei (2020) concluded that analysts typically rate overvalued equities more favorably than undervalued stocks and thus earn negative abnormal returns. The authors emphasized on the anomalies of stock market returns, indicating that analysts’ biases could be a contributor factor for financial market mispricing.

2.4. Value Creation of Analyst Recommendations

According to Grossman and Stiglitz (1980), equilibrium exists when information is not very costly, thus the market price will expose the majority of the information held by knowledgeable traders. According to general agreement, prices cannot accurately reflect the information that is available because, if they did, individuals who invested resources to collect it would not be compensated. As a result, they drew attention to the inherent tension between the incentives for information acquisition and market efficiency.

Womack (1996) found that buy and sell recommendations had large post-recommendation price drifts, and that small capitalization firms had higher excess returns. The author concluded that analysts seem to have the ability to stock pick and to time the market.

Barber, Lehavy, McNichols and Trueman (2001) stated that annual abnormal returns of more than 4% can be obtained by purchasing equities with the majority of positive analyst recommendations and shorting the stocks with the majority of negative recommendations.

2.5. Analyst Recommendations in Global Markets

Most of the studies in international markets covered only one country. Chakrabarti (2004) revealed that prices do not immediately adjust to incorporate all the information contained in analysts' reports in India. Therefore, these professionals outperformed the BSE national index during a four-month projected window from 1998 to 2003.

Jegadeesh and Kim (2006) pioneered the studies of analyst recommendation across different markets. They concluded that downgrade recommendations add more value than upgrade ones from analyst recommendations covering the G-7 countries from 1993 to 2002.

On the other hand, Azzi, Bird, Griringhelli and Rossi (2006) studied the recommendations in fifteen European markets and inferred that analyst suggestions do not offer any helpful information by analyzing a sample size from 1994 to 2004.

Balboa, Gomez-Sala and Lopez-Espinosa (2009) argued that recommendations are optimistically biased, with the United States and the United Kingdom being the nations with the highest levels of bias. The study concluded that countries with lowest bias achieve greater risk adjusted abnormal returns in terms of analyst recommendations.

Moshirian, Ng and Wu (2009) analyzed recommendations in thirteen emerging markets from 1996 to 2005. The authors demonstrated that increased informational asymmetries can be found in emerging markets, which allows investors to achieve abnormal returns by rapidly reacting to their suggestions.

2.6. Existing View on Analyst Recommendations

The existing literature in this field of study is, therefore, divided into two contradictory views: one that analyst recommendations do not add any value to investors, and the other that suggests that carefully selecting stocks to invest in can generate alpha. The proponents of the Efficient Market Hypothesis support the first view and believe that all the information is already included in a company's share prices. In addition, the implementation of technological advancements in trading has further contributed to their view. With the rise of algorithmic trading in recent times, the time in which information is processed into companies' share prices is significantly reduced. On the other hand, the critics of the Efficient Market Hypothesis argue that investors are subject to bounded rationality and that it is therefore possible to generate constant alpha over the long run by following analyst recommendations. Despite investors' level of discipline, they argue that investors frequently make financial decisions that are influenced by behavioral biases that lead them to act emotionally or process information incorrectly. Their reasoning heavily relies on the existence of market inefficiencies that arise because trades are conducted by humans or by computers that have been programmed by humans.

3. Methodology

3.1. Data Selection

The analyst recommendation data used in this research was extracted from the Bloomberg Terminal. A total of 155,742,780 recommendations were analyzed across ten different markets over the past 20 years. This research studied analyst recommendations separately across 5 developed countries (Australia, England, Germany, Japan and United States) and 5 developing countries (Brazil, Russia, India, China and South Africa). For each nation, stocks from one of the most widely used indices containing highly liquid stocks were selected:

- Australia: S&P/ASX 200 Index
- England: FTSE 100 Index
- Germany: Deutsche Boerse AG German Stock (DAX) Index
- Japan: Nikkei 225 Index
- United States: S&P 500 Index
- Brazil: Ibovespa Brasil Sao Paulo Stock Exchange Index
- Russia: MOEX Russia Index
- India: MSCI India Index
- China: Shanghai Shenzhen CSI 300 Index
- South Africa: MSCI South Africa Index

Since the members of these indices change over time, the study appropriately accommodates these alterations. In terms of the selection of developing countries, the strongest developed economies were picked across every continent, capturing different cultures. For the selection of the developing nations, the BRICS was used as it captures the most promising and fast-paced economies which international investors are constantly monitoring. Table I details

the number of analyst recommendations per developed country, whereas Table II breaks down the recommendations per developing nation.

3.2. Analyst Consensus

The data on analyst recommendations are on an ascending scale from 1 to 5, meaning that 1 is the strongest sell, 3 is a hold and 5 is the strongest buy. Among the stocks in the universe mentioned above, stock recommendations were analyzed on a daily basis over a 20-year time span, from November 2002 to November 2022. The following criteria were also imposed:

1. If the recommendation was issued on a non-trading day, the study assumed that it was issued on the next trading day.
2. Recommendations that have not been updated for a year or longer were excluded from the sample size.
3. Recommendations that required extra fees to be accessed were excluded from the sample.

The consensus ($\hat{A}_{i,t}$) was then calculated by aggregating, on a daily basis, the recommendations for each individual company that fit all the above criteria and doing an average weighted calculation as follows:

$$\hat{A}_{i,t} = \frac{1}{n_{i,t}} \sum_{j=1}^{n_{i,t}} A_{i,t,j}$$

Where:

$A_{i,t,j}$ = The recommendation from analyst (j) for each individual company (i) on day (t)

$n_{i,t}$ = The number of recommendations per company (i) on day (t)

3.3. Portfolio Selection

In this study, a daily buy signal was only considered if the stock had an average recommendation ($\hat{A}_{i,t}$) of 4.5 or above. The idea behind this selection was to determine whether

stocks that are consensually considered as strong buys actually end up outperforming the market or not. Since in theory, shorting a stock is riskier than going long, shorting stocks with recommendations of strong sell was not included in this study.

3.4. Calculating Returns

To measure the performance of analyst recommendations, a weighted-value portfolio for each country was constructed. The return ($R_{p,t}$) on each of these portfolios was calculated as follows:

$$R_{p,t} = \sum_{i=1}^{n_{p,t}} \frac{Mrkt\ Cap_{i,t}}{\sum_{i=1}^{n_{p,t}} Mrkt\ Cap_{i,t}} \ln \left(\frac{P_{i,t}}{P_{i,t-1}} \right)$$

Where:

$n_{p,t}$ = the number of firms in the portfolio at the close of the trading day (t)

$Mrkt\ Cap_{i,t}$ = the close price of the shares of firm (i) times its number of shares outstanding on day (t).

$P_{i,t}$ = the close price of the shares of firm (i) on day (t) adjusted for any corporate action On day (t).

For each portfolio, the average annual return, annual standard deviation, Sharpe Ratio, Skewness, Kurtosis, daily maximum and minimum returns and the number of positive and negative days were computed.

The average non-adjusted annual return was calculated by summing the daily returns of the portfolio, dividing that number per the total amount of trading days and then multiplying by 252 which is the number of trading days in a year. Comparing the average annual return of portfolios that implement different strategies is a misleading metric as it does not consider the level of risk undertaken by investors.

Therefore, the Sharpe ratio was calculated in order to compare the returns of the portfolios while adjusting for its level of risk. To do so, the daily returns for each portfolio were subtracted by the daily risk-free rate attributable to the specific market in which the stocks of the portfolios trade. Then, the average annual adjusted return was calculated using the same method as the non-adjusted average return described earlier. Additionally, the annual standard deviation was computed by calculating the average standard deviation of the daily returns and multiplying it by the square root of the number of trading days in a year. Thus, the Sharpe ratio was obtained by dividing the annual adjusted returns by the annual standard deviation.

The Skewness and Kurtosis were used to assess the distribution and variability of the data sample. The latter describes the distribution of the data around the mean, whilst the former quantifies the symmetry of the distribution of returns. In other words, high Kurtosis means that the distribution presents thicker tails and an even distribution, whilst low Kurtosis means that the distribution has thinner tails and a distribution more concentrated towards the average. A negative Skewness means that the data lies on the right side of the distribution, whilst a positive figure means that the data lies on the left side of the distribution.

3.5. Calculating Abnormal Returns

The analysis of abnormal returns was constructed separately for each of the portfolios mentioned above using three different models. The factors of each model were taken by the methodologies on Kenneth French's Website.⁴ For the United States, the factors used were taken from the U.S. (United States) Research Returns data. Similarly, for Japan, the factors were taken from the Japanese Research Returns data. In the case of England and Germany, the factors were taken from the European Research Returns Data. In other words, for these two European countries, although their stocks do not behave in the same manner, due to the lack of

⁴ https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

data available, the factors used were the same. For Australia, the factors used were from the Developed (ex-US) Research Returns Data. In the case of the five developing nations, the factors were taken from the Emerging Markets Research Return Data. Additionally, for the developing countries, the returns were aggregated monthly due to the lack of daily data on the factors for these countries.

3.5.1. Capital Asset Pricing Model

To begin, the Capital Asset Pricing Model (CAPM) was implemented to estimate the daily time-series regression:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + \epsilon_{p,t}$$

Where:

$R_{f,t}$ = Risk free rate (in which the daily 1-month T-Bill was used).

α_p = the estimated excess return of the portfolio (Jensen's Alpha).

β_p = the estimated systematic risk of the portfolio (Beta).

$\epsilon_{p,t}$ = the regression error term.

The estimation from the regression above gives insights into the characteristics of the enterprises included in each portfolio. The portfolio that yielded a positive (negative) β_p value contain enterprises that are, on average, riskier (less risky) than the market.

3.5.2. Multivariate Models

Following the implementation of the CAPM, this study also employed the Three Factor Pricing Model introduced by Fama and French (1993) plus the additional momentum factor. The daily time-series regression used in this case was as follows:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{p1}(R_{m,t} - R_{f,t}) + \beta_{p2} SMB_t + \beta_{p3} HML_t + \beta_{p4} WML_t + \epsilon_{p,t}$$

Where:

SMB_t = the daily return spread between a value weighted portfolio of small stocks and a value weighted portfolio of large stocks (the size factor)

HML_t = the daily return spread between a value weight portfolio of high book to market stocks and a value weighted portfolio of low book to market stocks (the value factor).

WML_t = the daily return spread between a value weight portfolio of winner stocks and a value weighted portfolio of loser stocks (the momentum factor)

In these estimations, portfolios that contain smaller (larger) companies yielded, on average, a positive (negative) β_{p2} . Moreover, portfolios that have a greater (smaller) allocation towards firms that have a high (low) book-to-market ratio presented, on average, a β_{p3} larger (smaller) than zero. Additionally, portfolios that contain winner (loser) stocks yielded, on average, a positive (negative) β_{p4} .

Lastly, the Five Factor Pricing Model developed by Fama and French (2015) was implemented with the addition of the momentum factor. This model was developed because the authors believed that the three-factor model was inadequate to explain expected returns as it overlooked the variation in average returns that were prevenient from profitability and investment. Therefore, Fama and French added two new factors. The Five Factor Plus Momentum model time series regression was estimated as follows:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{p1}(R_{m,t} - R_{f,t}) + \beta_{p2} SMB_t + \beta_{p3} HML_t + \beta_{p4} RMW_t + \beta_{p5} CMA_t + \beta_{p6} WML_t + \epsilon_{p,t}$$

Where:

RMW_t = the daily return spread between a value weight portfolio of the most profitable stocks and a value weighted portfolio of the least profitable stocks (the profitability factor).

CMA_t = the daily return spread between a value weight portfolio of firms that invest conservatively and a value weighted portfolio of firms that invest aggressively (the investment factor).

In this last regression, β_{p4} and β_{p5} were included. The former indicates that, on average, portfolios that yielded a positive (negative) β_{p4} contains more stocks of firms that are more (less) profitable. A value of β_{p5} greater (smaller) than zero, indicates that the portfolio is more inclined towards firms that invest more conservatively (aggressively).

Notably, the factors used on the regressions above were not used to indicate that they are risk factors. Instead, the models were utilized to determine if any superior performances are attributable to analysts' skills in stock selection or if they selected stocks that have traits that are known to cause favorable returns.

3.6. Transaction Costs

The excess returns obtained by the regressions do not include the expenses associated with trading. To analyze whether investors would be better off by following strong buy analyst recommendations, for the countries in which a statistically significant positive excess return is achieved, this study calculated the bid-ask spread costs associated with trading.

To estimate this value, first the daily turnover of the portfolios had to be calculated. The daily (t) turnover for each portfolio (p) equals the percentage of their stock holdings as of the close of the previous day (t-1) that has been liquidated as of the close of day (t).

To arrive at the correct number, four steps were taken. First, the percentage ($A_{i,t}$) that each stock in portfolio (p) that would have made up the portfolio at the conclusion of trading on day (t-1) in case there was no rebalancing was calculated. Mathematically:

$$A_{i,t} = \frac{m_{i,t-1} \left(\ln \left(\frac{P_{i,t}}{P_{i,t-1}} \right) \right)}{\sum_{i=1}^{n_{p,t-1}} m_{i,t-1} \left(\ln \left(\frac{P_{i,t}}{P_{i,t-1}} \right) \right)}$$

Where:

$m_{i,t} = \frac{Mrkt\ Cap_{i,t-1}}{\sum_{i=1}^{n_{p,t}} Mrkt\ Cap_{i,t-1}}$ = the close price of the shares of firm (i) times its number of shares outstanding on day (t-1) divided by the aggregate market capitalization of all firms in the portfolio on day (t-1).

Secondly, $B_{i,t}$ is determined as the actual portion of portfolio (p) that firm (i) makes up at the end of trading on date (t) considering the necessary rebalancing. Then, $B_{i,t}$ is subtracted from $A_{i,t}$. Lastly, the difference in the holdings of each day (t-1) is then added together, arriving at the daily portfolio turnover, $T_{i,t}$, given by:

$$T_{i,t} = \sum_{i=1}^{n_{p,t}} \max \{A_{i,t} - B_{i,t}, 0\}$$

Following the calculation of the portfolio turnover per day, the daily *Bid – Ask Spread* $_{p,t}$ was calculated as follows:

$$Bid - Ask Spread_{p,t} = \sum_{i=1}^{n_{p,t}} \left(\frac{Ask Price_{i,t} - Bid Price_{i,t}}{Ask Price_{i,t}} \right)$$

Where:

$Bid Price_{i,t}$ = the highest price of security (i) on day (t) that an investor will accept to pay for a security.

$Ask Price_{i,t}$ = the lowest price a broker will accept to sell a security (i) on day (t).

Finally, multiplying the daily portfolio turnover ($T_{i,t}$) by the daily *Bid – Ask Spread* $_{p,t}$ allowed this study to estimate the minimum transaction costs for the portfolio that generated positive alphas, assuming no commission fees.

4. Discussion

4.1. Sample Characteristics

Based on Table I, the total number of analyst recommendations in the United States is far greater than in any other country. That is due to the greater number of average stocks analyzed per day. When it comes to the average number of recommendations that were analyzed per day and per stock, Germany is the country with the greatest number of total recommendations, followed by India and then the United States.

It is worth noting that, in accordance with the literature mentioned above, sell-side analysts are reluctant to issue sell recommendations which might be an appealing argument that these experts are overconfidently biased. During the 20-year time range studied, Table II shows that the number of consensus buys is far greater than the number of sell recommendations for all the countries analyzed. In China, for example, the country with the biggest difference between those two figures, analysts recommended approximately 24 times more purchase issues than sell suggestions. The country with the least spread between these figures was South Africa, with buy recommendations exceeding sell calls by almost 369 percent. Analysts in the United States, a market that is a reference in terms of stock market development, suggested approximately 17 times more buys than sells. Among the developed countries, Australia was the one with the least percentage difference between buy and sell suggestions.

The greatest average annual return was recorded in India, with strong buy recommendations registering a 22.26 percent average return per year. However, when subtracting the risk-free rate from this figure, the portfolio achieved a negative average annual return of 0.92 percent with a Sharpe ratio of negative 0.05. On the other hand, Japan registered the lowest average annual return of negative 3.09 percent. The highest average annual returns above the risk-free rate were achieved in South Africa and Germany, with a figure of 14.83 and 14.25 percent, respectively. Analyst recommendations of German stocks achieved the highest Sharpe ratio of 0.69. In the United States, the Sharpe ratio obtained was 0.29.

4.2. Developed Countries

In the univariate model performed to assess the effect of strong buy analyst recommendations in Australia, the estimated intercept equals 0.02. Therefore, the Capital Asset Pricing Model suggests that the strategy of following strong buy analysts' recommendations for companies within the S&P/ASX 200 Index yields an excess return of 0.02 percent. However, the coefficient is not statistically significant under any conventional level as per the

p-value and t-statistic of 0.19 and 1.32, respectively, suggesting that there might be other confounding factors that influence the returns of this strategy. When implementing the Three Factor Pricing Model Plus Momentum, the alpha increases to 0.03 percent and becomes statistically significant under a 10 percent significance level (p-value 0.083). Likewise, the Five Factor Pricing Model Plus Momentum estimates alpha at 0.031 percent and preserves the statistical significance with a p-value of 0.071. Therefore, the estimate from the CAPM seems to be negatively biased, and including additional factors eliminates the omitted variables bias. Table V shows the estimated coefficients for all three models applied to strong buy recommendations for the S&P/ASX 200 Index and their respective p-values results.

In England, the coefficient that measures the excess return for all the models was around 0.03 percent, although including additional factors lowered alpha slightly, to 0.028 and 0.025 percent, respectively. However, none of the models were statistically significant at any conventional level. Table VI reports on the regression results from the respective three models applied to strong buy recommendations for FTSE Index.

German strong buy suggestions yielded an excess return of around 0.04 percent for all three models studied. Additionally, as per the p-value of around 0.02 and t-statistics of around 2.3 for all three models, the coefficients are statistically significant at 10 and 5 percent levels. In this case, including additional factors did not significantly change the estimates nor influenced the statistical significance. Table VII shows the estimated coefficients and their p-values.

In Japan, CAPM yielded an excess return of negative 0.017 while the Three and Five Factor Plus Momentum models estimated it at 0.009 and 0.007, respectively. However, none of the models were statistically significant at any conventional level. The results for Japan are shown in Table VIII.

In the United States, the excess return of the portfolio of strong buy recommendations yielded an excess return of around negative 0.02 percent for all three models. In all the regressions, the coefficients were statistically significant under all conventional levels. Accounting for additional factors did not significantly influence the results obtained in the CAPM model. Therefore, investors are better off investing in a passive investment strategy that tracks the S&P 500 Index than following strong buy analyst suggestions in the United States. Table IX shows the estimated coefficients and their p-values.

4.3. Developing Countries

In Brazil, the obtained estimated coefficient of the CAPM was negative 0.178. Moreover, when accounting for other factors, the strategy yielded a return of negative 0.512 and 0.531, for the Three Factors Plus Momentum Model and for the Five Factors Plus Momentum model, respectively. Although including the additional factors lowered p-values from 0.7 to 0.3, none of the three models computed an excess return that was statistically different from zero under any conventional level. Table X shows the results for the estimated alpha generated from strong buy recommendations of the Ibovespa Index.

Interestingly, for Russia, the alpha obtained from the CAPM regression was negative 0.155, while the Three Factors Pricing Model Plus Momentum and the Five Factors Model Plus Momentum yielded positive returns of 0.355 and 0.626, respectively. However, including additional factors did not improve the p-values and therefore all three models yield a result that is not statistically significant at any conventional level, as shown in Table XI.

On the other hand, the results obtained from all three models were statistically significant in India, as shown in Table XII. The excess return achieved by strong buy recommendations in India was around negative 0.08 percent for all three models, concluding that this type of purchase suggestions do not add value to investors that invest in Indian stocks.

Meanwhile, in China, the estimated alpha from the CAPM was 0.219, while including other factors resulted in a decreased estimated alpha of 0.131 and 0.164 percent, respectively for Three Factors Pricing Model Plus Momentum and the Five Factors Model Plus Momentum. Similarly, to Russia, none of the models resulted in a statistically significant coefficient, shown in Table XIII.

In South Africa, the country with the lowest difference among the amount of buy and sell suggestions, the estimated excess return by the CAPM was 0.842 and was statistically significant under the 10 and 5 percent significance levels. When accounting for other factors, as per Three Factors Pricing Model Plus Momentum the coefficient obtained was 0.855 which was statistically significant under the 10 percent level. In the Five Factors Model Plus Momentum, the coefficient became statistically significant under the 5 percent conventional level and the estimated alpha was 0.943 percent. Detailed results are shown in Table XIV.

4.4. Outperformers

As mentioned previously, the strategy of following strong buy analyst recommendations in Australia, Germany and South Africa yielded a statistically significant positive excess return. However, these returns did not include the expenses associated with trading. Following the previously discussed methodology for estimating transaction costs, the minimum transaction cost was around 0.022, 0.0027 and 0.06 percent of the daily market value of these portfolios, respectively. The variation in these numbers is directly related to the liquidity of these stocks and to the frequency in which the portfolios were rebalanced in these countries. In other words, stocks with greater liquidity presented narrower spreads, thus the bid-ask cost of trading these securities is lower. Also, the portfolios that required a more frequent rebalance had to pay these spreads more frequently, thus dragging the excess return lower.

After accounting for this cost, the strategy of following strong buy analyst recommendations in Australia yielded an excess return of 0.0094 percent, while in Germany and South Africa, the excess return obtained was 0.015 percent and 0.833, respectively.

5. Limitations

Even though the analysis on the effectiveness of strong buy analyst recommendations was thoughtfully designed, it had its limitations and requires further study. Most problems were caused by data limitations, particularly because the same factors had to be used across different markets due to the limitations in available data for these countries. However, countries have particular characteristics that might explain their stock market returns. Therefore, as it can be seen from Tables V to XIV, the R-square for the portfolios that used general factors that were not exclusively particular to their market, obtained low levels of this figure. In other words, the independent variable variation could not explain the variation in the dependent variable. Additionally, in terms of the transaction costs, only the bid-ask spread was calculated. Due to the limits on the availability of commission costs in the three countries in which a significant positive alpha was computed, it was not possible to calculate the real transaction costs that investors face. Therefore, the alpha presented was overstated.

In order to further improve this study, for each market, the best confounding factors need to be identified in order to obtain statistically significant coefficients that measure the excess return of strong buy analyst recommendations across the different markets studied. Furthermore, in order to better compare the strategy of following strong buy analyst recommendations to the buy and hold strategy, investors should account for all the additional transaction costs incurred in the increased level of their trading activity.

6. Conclusion

Numerous experts search the market for securities that are under-priced and issue new recommendations in a daily basis. Therefore, the purpose of this study was to analyze whether the most highly recommended stocks add value to local investors or can be used to reliably compare the returns of investors' own strategies. Contrary to many other studies in the industry, this paper did not use any data mining techniques as it focused on exploring ex-ante strategies that would be valuable to investors worldwide.

Even though the daily returns for all the portfolios registered more positive than negative days, none of the portfolios achieved a Sharpe ratio figure higher than one. In other words, the returns achieved by strong buy analyst recommendation did not justify the risk undertaken by analysts. Therefore, for every country, this study began using the Capital Asset Pricing model and then used the Three Factor Model Plus Momentum followed by the Five Factor Model Plus Momentum to control for the well-known factors that affect these markets. The results of these regressions shed light on the abnormal returns that were to be achieved in case investors were to follow analysts strong-buy recommendations.

The empirical evidence from this study contradicts the straightforward and widely accepted theory that security analysts do not consensually spot mispriced stocks. Indeed, in the countries in which the ratio of buy and sell recommendations was large, analyst recommendations did not provide any value. Therefore, investors in these countries are better off by passively investing in Exchange Traded Funds that track their markets' index than by following the highest rated stocks according to sell-side securities analysts. However, for the countries in which buy suggestion exceed sell recommendations by less than five hundred percent, it was concluded that analyst recommendations add value even after accounting for transaction costs. Thus, it can be concluded that the behavioral biases of analysts, particularly overconfidence, have a discernible influence on the value of their suggestions.

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Appendix

Table I: Descriptive Statistics per Developed Country

Developed Countries	Australia	England	Germany	Japan	United States
Total Number of Analyst Recommendations	12,483,830	11,911,128	7,427,526	19,082,358	60,969,849
Number of Recommendations per day	1,709	1,630	1,017	2,612	8,345
Number of Recommendations per Day and per Stock	9	16	25	12	17
Total Average Recommendations	1,034,522	655,879	246,681	1,556,596	3,272,247
Average Recommendations Above 4.5	133,658	72,179	18,028	162,904	445,832
Average Recommendations Above 3	796,383	558,035	208,156	1,261,133	2,988,303
Average Recommendations Below 3	162,363	77,118	36,456	192,032	179,430
Average Recommendations Equal to 3	75,776	20,726	2,069	103,431	104,514
Difference of Buy and Sell Recommendations	4.90x	7.24x	4.76x	6.57x	16.66x

Table II: Descriptive Statistics per Developing Country

Developing Countries	Brazil	Russia	India	China	South Africa
Total Number of Analyst Recommendations	5,752,236	2,002,237	17,357,915	16,485,817	2,269,884
Number of Recommendations per day	787.33	274.05	2,375.84	2,256.48	310.69
Number of Recommendations per Day and per Stock	9	6	22	8	8
Total Average Recommendations	461,267	200,267	640,226	1,214,794	226,821
Average Recommendations Above 4.5	114,781	56,510	144,078	631,253	24,494
Average Recommendations Above 3	410,592	167,773	563,973	1,138,140	164,246
Average Recommendations Below 3	32,933	21,140	63,441	47,865	44,473
Average Recommendations Equal to 3	17,742	11,354	12,812	28,789	18,102
Difference of Buy and Sell Recommendations	12.47x	7.94x	8.89x	23.78x	3.69x

Table III: Descriptive Statistics of the Portfolios per Developed Country

Developed Countries	Australia	England	Germany	Japan	United States
Avg Annual Return	11.32%	5.46%	12.46%	3.09%	5.78%
Avg Annual Return Above RF Rate	9.96%	8.99%	14.25%	1.12%	4.83%
Standard Deviation	20.50%	21.19%	20.68%	20.17%	17.41%
Sharpe Ratio	0.49	0.42	0.69	0.06	0.28
# of Positive days	53%	53%	52%	51%	54%
# of Negative Days	47%	47%	48%	49%	46%
Daily Skewness	-0.95	-1.79	-0.33	-0.09	-0.57
Daily Kurtosis	14.75	33.54	11.38	9.38	15.57
Daily Maximum	10%	13%	15%	14%	12%
Daily Minimum	-16%	-25%	-13%	-12%	-14%

Table IV: Descriptive Statistics of the Portfolio per Developing Country

Developing Countries	Brazil	Russia	India	China	South Africa
Avg Annual Return	10.76%	10.50%	22.26%	11.85%	21.56%
Avg Annual Return Above RF Rate	7.44%	7.17%	-0.92%	10.09%	14.83%
Standard Deviation	28.04%	27.48%	19.93%	21.43%	25.78%
Sharpe Ratio	0.27	0.26	-0.05	0.47	0.58
# of Positive days	52%	52%	55%	52%	52%
# of Negative Days	48%	48%	45%	48%	48%
Daily Skewness	-0.86	-2.21	-0.91	-0.29	0.21
Daily Kurtosis	25.71	96.61	13.77	7.48	10.32
Daily Maximum	18%	31%	11%	9%	19%
Daily Minimum	-26%	-44%	-16%	-10%	-14%

Table V: Regression Results of Strong Buy Recommendations of the S&P/ASX 200 Index.

Australia	CAPM	3F + Momentum	5F + Momentum
ALPHA	.023 (.185)	.03* (.083)	.031* (.071)
MKT-RF	.365*** (0)	.214*** (0)	.159*** (0)
SMB		-.562*** (0)	-.597*** (0)
HML		-.116** (.017)	.095 (.137)
RMW			.025 (.779)
CMA			-.531*** (0)
WML		.023 (.473)	.067** (.043)
Observations	5188	5188	5188
R-squared	.076	.104	.111

p-values are in parentheses

*** $p < .01$, ** $p < .05$, * $p < .1$

Table VI: Regression Results of Strong Buy Recommendations of the FTSE Index.

England	CAPM	3F + Momentum	5F + Momentum
ALPHA	.03 (.124)	.028 (.147)	.025 (.186)
MKT-RF	.001 (.94)	.007 (.735)	-.022 (.328)
SMB		.067 (.156)	.044 (.355)
HML		.139*** (.001)	.302*** (0)
RMW			.232*** (.004)
CMA			-.233*** (.003)
WML		.024 (.397)	.027 (.345)
Observations	5188	5188	5188
R-squared	0	.003	.007

p-values are in parentheses

*** $p < .01$, ** $p < .05$, * $p < .1$

Table VII: Regression Results of Strong Buy Recommendations of the DAX Index.

Germany	CAPM	3F + Momentum	5F + Momentum
ALPHA	.043** (.021)	.042** (.024)	.042** (.026)
MKT-RF	-.016 (.284)	-.023 (.254)	-.049** (.025)
SMB		-.027 (.56)	-.048 (.3)
HML		.053 (.2)	.157*** (.003)
RMW			.081 (.307)
CMA			-.226*** (.003)
WML		.047 (.165)	.06* (.086)
Observations	5188	5188	5188
R-squared	0	.001	.003

p-values are in parentheses

*** $p < .01$, ** $p < .05$, * $p < .1$

Table VIII: Regression Results of Strong Buy Recommendations of the Nikkei 225 Index.

Japan	CAPM	3F + Momentum	5F + Momentum
ALPHA	-.017 (.187)	-.009 (.463)	-.007 (.557)
MKT-RF	.901*** (0)	.832*** (0)	.82*** (0)
SMB		-.438*** (0)	-.434*** (0)
HML		-.195*** (0)	-.159*** (0)
RMW			-.137*** (.003)
CMA			-.208*** (0)
WML		.095*** (0)	.13*** (0)
Observations	5186	5186	5186
R-squared	.607	.632	.634

p-values are in parentheses

*** $p < .01$, ** $p < .05$, * $p < .1$

Table IX: Regression Results of Strong Buy Recommendations of the S&P 500 Index.

United States	CAPM	3F + Momentum	5F + Momentum
ALPHA	-.02*** (.003)	-.021*** (0)	-.02*** (0)
MKT-RF	.989*** (0)	1.048*** (0)	1.032*** (0)
SMB		-.163*** (0)	-.153*** (0)
HML		-.211*** (0)	-.12*** (0)
RMW			.035*** (.008)
CMA			-.356*** (0)
WML		.07*** (0)	.098*** (0)
Observations	5009	5009	5009
R-squared	.868	.9	.908

p-values are in parentheses

*** $p < .01$, ** $p < .05$, * $p < .1$

Table X: Regression Results of Strong Buy Recommendations of the Ibovespa Index.

Brazil	CAPM	3F + Momentum	5F + Momentum
ALPHA	-.178 (.683)	-.512 (.277)	-.531 (.273)
MKT-RF	.902*** (0)	.756*** (0)	.771*** (0)
SMB		-.311 (.226)	-.3 (.252)
HML		1.011*** (0)	.977*** (.001)
RMW			.032 (.936)
CMA			.085 (.813)
WML		-.197 (.234)	-.2 (.238)
Observations	239	239	239
R-squared	.383	.442	.442

p-values are in parentheses

*** $p < .01$, ** $p < .05$, * $p < .1$

Table XI: Regression Results of Strong Buy Recommendations of the MOEX Russia Index.

Russia	CAPM	3F + Momentum	5F + Momentum
ALPHA	-.155 (.742)	.335 (.524)	.626 (.24)
MKT-RF	.873*** (0)	.887*** (0)	.725*** (0)
SMB		.292 (.308)	.157 (.586)
HML		-.405 (.117)	-.235 (.468)
RMW			-.871** (.045)
CMA			-.713* (.074)
WML		-.309* (.094)	-.227 (.224)
Observations	239	239	239
R-squared	.335	.351	.369

p-values are in parentheses

*** $p < .01$, ** $p < .05$, * $p < .1$

Table XII: Regression Results of Strong Buy Recommendations of the MSCI India Index.

India	CAPM	3F + Momentum	5F + Momentum
ALPHA	-.083*** (0)	-.079*** (0)	-.083*** (0)
MKT-RF	.008*** (0)	.008*** (0)	.009*** (0)
SMB		.007 (.208)	.008 (.124)
HML		0 (.933)	.002 (.686)
RMW			.018** (.026)
CMA			.001 (.858)
WML		-.005 (.124)	-.007** (.049)
Observations	239	239	239
R-squared	.11	.126	.144

p-values are in parentheses

*** $p < .01$, ** $p < .05$, * $p < .1$

Table XIII: Regression Results of Strong Buy Recommendations of the CSI 300 Index.

China	CAPM	3F + Momentum	5F + Momentum
ALPHA	.219 (.627)	.131 (.797)	.164 (.753)
MKT-RF	.722*** (0)	.783*** (0)	.774*** (0)
SMB		.181 (.512)	.169 (.55)
HML		-.219 (.378)	-.244 (.441)
RMW			-.148 (.728)
CMA			-.007 (.985)
WML		.205 (.25)	.218 (.233)
Observations	239	239	239
R-squared	.272	.281	.282

p-values are in parentheses

*** $p < .01$, ** $p < .05$, * $p < .1$

Table XIV: Regression Results of Strong Buy Recommendations of the MSCI South Africa Index.

South Africa	CAPM	3F + Momentum	5F + Momentum
ALPHA	.842** (.045)	.885* (.055)	.943** (.047)
MKT-RF	.451*** (0)	.563*** (0)	.534*** (0)
SMB		-.052 (.836)	-.078 (.761)
HML		-.675*** (.003)	-.654** (.023)
RMW			-.185 (.63)
CMA			-.121 (.732)
WML		.338** (.037)	.355** (.032)
Observations	239	239	239
R-squared	.144	.2	.201

p-values are in parentheses

*** $p < .01$, ** $p < .05$, * $p < .1$