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The Other Side of Equity Valuation

Unlock The Power of Expectations-Based Investing with a Reverse-Engineered Valuation Model

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Abstract

Corporate valuations models have extensive use in practice and are cornerstones in the academic setting of finance. Traditional valuation models have the function to calculate the intrinsic value of a company on the basis of the forecasted performance of a company. However, due to the inaccuracy of forecasts, there is a need to uncover the other side of equity valuation, namely the expectations-based approach. Our study treads on the rather unexplored academic landscape of expectation investing by analyzing the market's expectations on equities performance Return on Equity (ROE) through a reverse-engineered Residual Income Valuation model (RIV-model), with the aim of answering the question; Can a reverse-engineered model be applied to assess the reasonableness of market valuation for investment purposes? To answer the research question, we performed a cross-industry analysis of the constituents in the S&P 500 index between the years 2011 to 2016 in an initial study, as well as a study of the latest financial figures of the year 2022. The results from the 1 803 observations of the two studies were that the model could be used to analyze the reasonableness of the market's expectations and that we could infer that markets were overvalued, with the exception of the Consumer Staple industry that was consistently undervalued according to our model.

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Acronym list

AP: Accuracy Parameter

BP: Basis Points

CAPM: Capital Asset Pricing Model

COE: Cost of Equity

DCF: Discounted Cash Flow

DDM: Dividend Discount Model

EMH: Efficient Market Hypothesis

EPS: Earnings Per Share

IPO: Initial Public Offering

IRR: Internal Rate of Return Model

RIV: Residual Income Valuation

ROE: Return on Equity

RP: Reasonableness Parameter

S&P 500: Standard & Poor's 500

1. Introduction

"Price is what you pay; value is what you get." — Warren Buffett, 2009

1.1. Background

Equity markets cover 105.07 trillion U.S. dollars in market capitalization (Statista, 2022), needless to say, many market participants are trying to get an edge in the market in order to generate a satisfactory return. As a tool for their efforts, there are many corporate valuation models available that investors and analysts can choose from to identify potential investments. These models should guide investors in how to invest their capital effectively while ensuring that the companies receive the funding they need to thrive. The ability to quickly access capital from the general public is a vital component for the growth of a company, which in turn plays a crucial role in driving economic development. Major companies across several industries, for example retailers like Walmart, Amazon, and Hennes & Mauritz are traded on the public stock exchanges (Investopedia, 2023), entailing that the market has a significant impact on their decision-making. The public equity market is thereby a part of shaping the future and the development of society. This underscores the importance of making well-informed investment decisions, which can be obtained by applying corporate valuation models.

Many corporate valuation models are used to calculate the intrinsic or fundamental value of equities. As stated by Buffett "Intrinsic value can be defined simply: It is the discounted value of the cash that can be taken out of a business during its remaining life" (Buffett, 2000, p. 60). Accordingly, investors with a fundamental focus tend to apply traditional models like the Dividend Discount Model (DDM) to determine a company's intrinsic value. Another fundamental valuation model is the Residual Income Valuation (RIV)-model, an accounting-based alternative, which has received more attention over the years (Penman & Sougiannis, 1998). However, the common factor among all fundamental valuation models is that forecasting lies at the very heart of the analysis. Not only is forecasting a time-consuming practice but it has also been revealed in research to have limited accuracy (Loh & Mian, 2006). This suggests a need to uncover another aspect of equity valuation. By shifting focus from an exact calculation of a company's intrinsic value to the general expectations of the market, another side of equity valuation can be unlocked.

Considering the field of equity valuation, one can argue that the theoretical literature on corporate valuation models is extensive, yet not complete. More specifically, little attention has been devoted to expectations investing and reverse-engineered valuation models. A reverse valuation model allows investors to distinguish if a stock is overvalued or undervalued, but removes the complex step of forecasting. The key conceptual difference between traditional corporate valuation models and reverse-engineered valuation models is that the former generates an intrinsic value of the analyzed company, while the latter instead generates the underlying market expectations of the firm's performance in terms of for example "critical cash flow" or return on equity (ROE). Thereby allowing investors to understand the market's current implied expectations. In addition, it is called a reverse model because it uses a traditional model but starts with the end-value, i.e. the market price, suggesting a fundamental shift in how to approach valuation. In one way, more similar to estimating the yield to maturity on a bond using market values and coupon payments (Cogliati, Paleari, & Vismara, 2008). More exactly, it shares the same underlying logic where all parameters are specified at the valuation date except the selected parameter such as cost of equity (COE), growth rate, or ROE.

Reverse-engineered valuation models have several advantages over traditional corporate valuation models. In addition to the aforementioned freedom from forecasting, a reverse model yields more intuitive results, even for investors without extensive knowledge and experience in valuation (Takács, Ulbert & Fodor, 2019). The results from the model can have several practical implications for capital market stakeholders: Firstly, by comparing the market expectations with the historical performance investors can determine the reasonableness of the market's expectations and decide if an in-depth analysis of the underlying business is relevant to conduct. Secondly, managers can gain an understanding of the current expectations implied by the market. From this, strategic capital allocation decisions can be attained such as when a company should buy back shares, issue new shares, or pay off debt.

Currently, expectation investing is not widely used in practice but there are examples. New Construct, an equity research firm that profiles itself as an expectations investor, provides research that demonstrates the practical application of the expectation investing approach (Trainer, 2022). One of the firms they have on their watchlist is Tesla which they have analyzed up until 2030. To estimate Tesla's valuation, they assume a base case of 26 million global electric vehicle sales by 2030, as projected by the International Energy Agency. The researchers then calculate the number of electric vehicles Tesla would need to sell to justify its current stock price, assuming different average selling prices for its vehicles. According to their reverse Discounted Cash Flow (DCF)-model, the market assumes that Tesla will achieve profit margins 1.5 times higher than Toyota Motor Corp and triple its current auto manufacturing efficiency to achieve its projected growth. Moreover, the results from the model suggest that Tesla's current stock price implies that the company will own 57% of the global passenger electric vehicle market in 2030, based on the aforementioned assumptions. This implies that the market is pricing in a significant level of growth for Tesla, even with increased competition from incumbent automakers. Further, Tesla's share of the global electric vehicle market fell from 16% in 2019 to 14% in 2021, indicating that the market share is declining rather than increasing. Based on the analysis, New Construct concludes that Tesla is significantly overvalued (Trainer, 2022).

Expectations investing can also have implications on the historical discussion on the rationality of investors and the efficiency of capital markets. The efficient market hypothesis (EMH) proposes that the market on average has an accurate conception of the value of equities and that this value is reflected in the share price (Fama, 1970). This has been challenged by practitioners and academics alike. World famous investor Warren Buffett has entered the debate on several occasions saying: “It’s crucial to understand that stocks often trade at truly foolish prices, both high and low. Efficient markets exist only in textbooks. In truth, marketable stocks and bonds are baffling, their behavior usually understandable only in retrospect” (Buffett, 2023, p. 4). Benjamin Graham, a well-renowned academic and author of the best-seller *The intelligent investor*, created an allegory for the relationship between investors and the market; personified in Mr. Market, a bipolar business partner who presents offers to trade shares at a given price each day (Graham, 1949). As an investor, it is therefore crucial to understand the underlying expectations of their business partner, i.e. Mr. Market, in order to make thoughtful investment decisions. Worth noting is that expectations investing and reverse-engineered models does not directly challenge the EMH, but rather is a tool to get the underlying expectations of the market. However, from the New Construct example above it is abundantly clear that the market does not have rational expectations for all companies at all times and thus reverse-engineered models can and are used to challenge the EMH.

1.2. Motivation and Purpose

We see potential for practical investment benefits by using a reverse valuation model to help investors investigate the reasonableness of the market's expectations. The reasonableness of the market expectations is especially relevant since it has been established that variation in stock prices is not fully reflected by fundamental factors, implying that other speculative aspects could be incorporated into stock prices (Cutler, Poterba & Summers, 1989). Accordingly, we strive to find a parameter that can identify the reasonableness of the market expectations because it would afford investors a tool for determining the overvaluation and undervaluation of equities. The parameter will thereby provide actionable insights which can be used to guide investors in their investment decisions.

In addition to our practical motivation, we are interested in expanding the research on reverse-engineered valuation models. This is especially relevant due to the relative scarcity of research within the field in comparison to the available research on other traditional valuation models such as the DCF-, and RIV-model. Currently, there are a limited number of academic studies exploring the concept of a reverse RIV-model, but with a different purpose compared to our model. Easton, Taylor, Shroff and Sougiannis (2002) applied a reverse RIV-model to estimate the expected COE and growth rate implied in the current market price, book values, and in a four-year analyst forecast of accounting earnings. From a conceptual standpoint, it is a fundamental shift since the reverse RIV-model does not generate an intrinsic value of a stock as the RIV-model presented by Ohlson (1995). However, the model presented by Easton et al. (2002) still relies on a forecast, which impacts the accuracy (Dreman & Berry, 1995). Further, in the Easton and Monahan (2005) study, the models tested were subject to several limitations such as a short explicit period. Therefore, we believe our model will contribute with a novel perspective to the literature on reverse-engineered valuation models by extending the explicit period, not relying on analyst forecasts and investigating the reasonableness of the market valuation.

1.3. Research Question

In this thesis we will apply a reverse-engineered RIV-model to investigate if the market has accurate expectations of companies' performance in terms of ROE. Subsequently, these expectations will be used to evaluate the reasonableness of the market valuation by comparing the expectations to the actual performance of the companies.

The aim of the study is therefore to answer the following question:

Can a reverse-engineered model be applied to assess the reasonableness of market valuation for investment purposes?

The research question can further be posed twofold as in; did the market *have* reasonable expectations during a selected period, and *has* the market reasonable expectations for the future. We will aim to approach both of these perspectives through the following two subquestions.

1) Did the market have accurate expectations of equities performance between the years 2011 to 2016?

2) Is it possible to create an accurate *prospective* parameter for the reasonableness of the market's future expectations?

1.4. Disposition

The subsequent chapters of the thesis are structured in the following way. Chapter 2 constitutes a literature review of theory and findings from previous research about the market's efficiency, available corporate valuation models, limitations of forecasting, expectations investing, and reverse-engineered valuation models. In chapter 3, the theoretical framework of the RIV-model as well as arguments for why this model is relevant is presented. Further, chapter 4 goes through the method, the assumptions made and the construction of two parameters used to evaluate the model results. In chapter 5, the data collection process and the final sample is presented. Moreover, chapter 6 presents the results to the reader which then is put into context in the discussion of chapter 7. Finally, the conclusion and suggestion for future research is presented in chapter 8.

2. Literature Review

Our thesis is related to several streams of corporate valuation literature. First, the EMH is discussed and challenged by the field of behavioral finance which explores cognitive biases and the limits to arbitrage. Thereafter, the reader will briefly be introduced to different models pertaining to “sophisticated” or “unsophisticated” valuation methods. Further, our thesis builds on the studies on the application of discounting for valuation purposes and thus the focus is devoted to how the concept has evolved over time and its relevance for the RIV-model. Moreover, forecasting and its related limitations will be discussed, with a particular emphasis on inaccuracy. The reader will then be introduced to the concept of expectations investing and how this approach can cope with the problems related to forecasting. Moreover, a special interest is devoted to reverse-engineered valuation models which is the first part of the expectations investing process. More specifically, previous research and applications of the reverse DCF- and RIV-model will be presented. The literature review will conclude by contextualizing our thesis in relation to previous research.

2.1. The Markets Efficiency and Ability to Find the Intrinsic Value

In the theory of finance, the EMH is often a cornerstone to most models and analyses. Under efficient markets, any stock price should always equal the present value of its future expected dividends, cash flow or residual income. The EMH is therefore based on the idea that the market is always rational and values companies based on fundamentals, entailing that market prices are always fair and reasonable (Fama, 1970). Accordingly, investors should not be able to earn abnormal returns due to the unpredictability of prices i.e. the random walk, and the competitive nature of a frictionless market. In this view, mispricing should not occur or immediately be adjusted by sophisticated investors in the market (Malkiel, 2003). However, this presumes that all information is freely available and directly reflected in the stock price, which is not descriptive of capital markets in practice. Cutler et al. (1989) argue that speculative components relative to the fundamentals play a significant role in explaining stock prices. The result indicates that up to half of the variance in stock prices cannot be explained by the fundamentals. Thus, the theoretical and empirical evidence of EMH has been challenged during the years (Shleifer, 2000).

From this view, behavioral finance has emerged which assumes that financial markets are informationally inefficient. More specifically, behavioral finance has two building blocks, cognitive psychology and the limits to arbitrage (Barberis & Thaler, 2003). Accordingly, investors are prone to several cognitive biases which impact their ability to make optimal investment decisions. Some examples are the overreaction hypothesis which entails that investors have a short-term focus and overreact to the most recent financial information (DeBondt & Thaler, 1987). Another cognitive bias is overconfidence which implies that investors typically overestimate their ability to forecast and analyze data (Daniel, Hirshleifer & Subramanyam, 1998). This gives rise to systematic behavior in the market, which in turn affects stock prices (Barberis & Thaler, 2003). Further, the limits to arbitrage suggest difficulties for rational investors to undo the drift in stock prices caused by less rational investors. Thus, investors are not always fast at imposing stock prices toward fundamental values, especially not when irrational investors are present in the market (Shleifer & Vishny, 1997). Therefore, behavioral finance suggests that sustained mispricing could be prevalent in the market.

2.2. Types of Corporate Valuation Methods

There are many different available valuation methods for investors and analysts to choose from when valuing companies. These methods can be categorized as either “sophisticated” or “unsophisticated” valuation methods (Barker, 1999). “Unsophisticated” valuation methods also referred to as the market-based approach is valuation using multiples such as the P/E ratio for valuing equity or EV/EBIT to value a firm's enterprise value (Berk & DeMarzo, 2017). Many investors prefer multiples since it is simpler and does not require forecasting of future cash flows. However, the market-based approach has several limitations. For instance, it provides a relative valuation that is in relation to comparable firms. This implies that the analysis is not anchored in the fundamentals of the firm's performance, instead, it assumes that the market is efficient in setting prices for the comparables (Barker, 1999). Consequently, this exercise becomes especially doubtful if firms are mispriced (Penman, 2003).

Accordingly, the theoretical literature favors “sophisticated”, which is based on the net present value of the expected financial performance of multiple future periods (Barker, 1999; Penman, 2003; Copeland, Koller & Murrin, 2000). The DDM is often regarded as the simplest version of the available equity valuation models. It builds on the present value rule, i.e. the asset's intrinsic value is the present value of the expected future dividend discounted at an appropriate discount rate (Damodaran, 2012). The two basic inputs in the general dividend discount model are the expected dividend and the COE. The expected dividend is based on assumptions about the future growth rate in earnings and the payout ratio. The RIV-model is also popular and it originates from the DDM, but the focus has been shifted to book values and earnings. Accordingly, the firm value equals the sum of its current book value of owners' equity and the present value of its future residual income. The most important contribution, at least to the fundamental valuation research in academia is the RIV-model presented by Ohlson (1995) and Feltham & Ohlson (1995), which led to a reexamination of the relation between accounting numbers and firm value (Bernard, 1995).

2.2.1. Discounting for Valuation Purposes

The previously mentioned "sophisticated" valuation models rely on the concept of discounting. The father of value investing, Benjamin Graham, chronicled a paradigm shift in equity valuation following the great market crash in the 1930s, from an emphasis on historical values to a focus on future earnings, i.e. discounting of future cash flow (Graham & Dodd, 2009). Even though Graham saw and chronicled this shift, he as an investor still focused on the historical perspective, i.e. the balance sheet. Warren Buffett, Graham's student, has on several occasions criticized his mentor for his focus on the balance sheet and tangible book value and low emphasis on growth and the future of the company. Buffett is instead keen on understanding and investing in companies with a competitive edge because of the stability and continuity of the future cash flows from these companies (Pecaute & Wrenn, 2017).

The early discount models were often subject to limitations; with only one term in the expression and not regarding terminal values and steady state phases (Williams, 1938). Later model iterations like the Gordon Model, which is still in use today, utilize a terminal value that considers the value of the company after the forecasted period (Gordon, 1959). With regards to the RIV-model, the projection of residual income is limited to a finite period, and thus the model has been developed into several versions where a second term is introduced i.e. the terminal value (Ohlson & Zhan, 1999). However, the explicit period's forecast of future payments to shareholders is still of utmost importance for the intrinsic value calculation.

2.2.2. Brief on Forecasting and its Accuracy

Most of the corporate valuation models today, including the RIV-model, require forecasting to get the figures to discount. Additionally, forecasts make it possible to adapt to the dynamics of industries and contingencies companies face. The forecasted period is often called the explicit period and is typically the first term of many valuation models. Forecasting is therefore a widespread and time-consuming practice, and studies have also shown that the accuracy of these forecasts can extensively affect the profitability of stock recommendations (Loh & Mian, 2006). However, the importance of the conceptual differences between valuation models, such as the DCF-model and RIV-model, appears to be less significant than their ability to assist in projecting future earnings and fundamentals (Dichev & Tang, 2009). While equity analyst earnings forecasts are considered a valuable source of information for investors, their accuracy is often limited. Some research found that the average error in earnings per share (EPS) predictions can be up to 20% (Brown & Ball, 1967) and the average error has grown over time (Dreman & Berry, 1995). Moreover, research indicate that analysts tend to be optimistic rather than pessimistic in their predictions (Easton & Monahan, 2005).

2.3. Expectation Investing as a Solution to Inaccuracy of Forecasting

Understanding the expectations investing approach is useful for investors, especially when considering forecasting inaccuracy and the findings from the field of behavioral finance. Expectations investing takes the standpoint of what the current market price foretells of the implicit market valuation, meaning that the market's expectations can be obtained without forecasting (Rappaport & Mauboussin, 2003).

When forecasting a company's performance, analysts need to identify several operational parameters such as the company’s revenue growth, margins and earnings (Rappaport & Mauboussin, 2003). Expectations investing aims to illuminate the critical levels of these operational parameters, like long-term growth in earnings (Nekrasov & Ogneva, 2011) or “critical cash flow level” (Takács et al., 2019). These critical levels are extracted by reverse-engineering a conventional valuation model, like a RIV-model, with assumptions given by the market, such as price and cost of equity or through the company filings (Rappaport & Mauboussin, 2003).

There is solid proof that this approach is valid in order to understand the implied market expectations (Takács et al., 2019). However, in the result presented by Easton and Monahan (2005), the expectations some models provide do not correspond with the ex-post observation, i.e. the market expectations do not actualize in reality (Nekrasov & Ogneva, 2011). Hence, it seems that either some models are better at predicting market expectations or that the market expectations are unreasonable. Still, an investor can from this implied critical level either determine the reasonableness of the levels, as the Tesla example in the introduction illuminates, or identify potential revisions to the expectations. Rappaport and Mauboussin (2003) suggest that investors should apply an "expectations infrastructure" which entails looking at potential scenarios where the market's expectations are out of line with the scenario. In this way, valuation and competitive strategy are incorporated into the valuation process which is necessary to make a thoughtful analysis of a business. Entailing that investors using an expectation investing framework still need to make a thorough business analysis to make a well-founded investment decision, but are not required to come to an exact figure for the estimate.

2.4. Reverse-Engineered Valuation Models

Expectations investing and reverse-engineered valuation models have primarily been used to study analyst forecasting or market expectations, in terms of accuracy and implied assumptions, as well as mispricing and subsequent market corrections. Worth noting is that the models use different data and assumptions, with the main methodological difference being the usage of either data from analyst forecasts or data provided by the company filings and the market price or market capitalization. A summary of the previous reverse valuation models included in the literature review is presented in Table 1.

2.4.1. Using Reverse-Engineered Models to Calculate Market Accuracy

The pioneering research article on reverse-engineered valuation models was conducted by Easton et al. (2002), who developed a reverse RIV-model and examined the long-term growth rate and implied COE for a portfolio of companies based on accounting data, market prices and four years consensus forecast. The author found that the equity risk premium was higher compared to the result from previous studies. What is unique with this study is that no assumptions are made regarding the growth rate in the residual income after the forecast period, rather the model estimates the price-implied growth rate. Albeit, the model was based on forecast data and does not therefore completely encapsulate the market expectations because analysts' data has a significant impact on the intrinsic value calculation. Thus, the model examines a combination of forecaster implications and market implications, and there is also a natural mix between the two since analysts have a substantial indirect impact on the market. Moreover, the assumptions and formation of the study are one of its main limitations. For instance, the length of the explicit period is assumed to be only four years and no adjustments for possible biases in the forecast data are incorporated. Thus, aligned with the view of the authors, the results should be interpreted with caution (Easton et al., 2002).

A later study conducted to examine the accuracy of the Easton et al. (2002) model and six other models, found that neither of the seven tested models yielded accuracy sufficient to have predictive power (Easton & Monahan, 2005). The study determined accuracy by comparing model estimates and ex-post observations. However, worth noting is that these models had several limitations with regard to the assumptions such as relying on a short explicit period. Moreover, later studies also show that the underlying assumptions and the source of data have a significant impact which could be an additional reason for the result presented by Easton and Monahan (2005). Accordingly, models that consider market estimations and observed earnings exhibit greater accuracy than those relying on analyst forecasts or target price; "Our paper suggests that methods based on realized earnings rather than earnings forecasts avoid the effect of bias in analysts' forecasts" (Easton & Sommers, 2007, p. 1013). The study by Easton and Sommers (2007) also suggests that analysts are biased toward optimism, which several other articles have found (Koller, Raj & Saxena, 2013; Easton & Monahan, 2005), at 2,84% in comparison to the equity risk premium of 3%. This suggests that relying on a forecasted outlook would remove the equity risk premium almost completely (Easton & Sommers, 2007).

Later studies use more relaxed assumptions and therefore become more accurate in the result due to improved adjustments to different settings. Nekrasov and Ogneva (2011) also investigate COE, but this study explores individual companies and can thus incorporate the firms' long-term growth as implied by data (Nekrasov & Ogneva, 2011). The model is therefore more flexible because it allows for consideration of firm-specific risks and outlook. These considerations are important both in the view that market participants and analysts incorporate them in their analysis, thus making the implied COE more reflective of the market expectations. Given the fact that companies face different risks and outlooks, the implied COE will be more adjacent to the realized COE. The model estimates in Nekrasov and Ogneva (2011) was found to have accurate estimations in relation to the ex-post observations implying improved performance in comparison to the original Easton et al. (2002) model.

The most advanced model uses analyst target price and EPS expectations to examine up to 3012 possible combinations of COE, long-term ROE, and long-term growth in the residual income model (Fitzgerald, Gray, Hall & Jeyaraj, 2013). Fitzgerald et al. (2013) do not look at the parameters implied by the market price but rather implied by the analyst target price and therefore diverging from the aforementioned models. This unconstrained approach uses a ten-year explicit period after which the firms are assumed to enter steady state. Thus, one limitation of this model is that it relies on analyst assumptions rather than the market's assumptions. In addition, there are three unknown parameters, resulting in a model with high complexity. However, in general, the model offers the most leeway and is closest to forecast estimates.

The reason for the difference in accuracy between the models, where accuracy is defined as a measure of the delta between model estimates and realized outcomes, has also been discussed in previous literature. Easton and Monahan (2005) put forward a theoretical framework for inaccuracy in expectations. They argued that the realized returns are equal to the expected return in addition to “surprise news” on cash flow and discount rate, meaning news after the fact and therefore not available as of the application of the model. Our interpretation of this explanation is the belief that markets or analysts have as a starting point reasonable expectations but due to the opaqueness of the future, revisions to the expectations have to be made on the basis of new information. Fitzgerald et al. (2013) argue that this is not the case and say that the reason why the expected equity risk premium of other models is 2-4% while the historic returns are 6%, is due to methodical reasons. They put forward that it is more consistent not to mix the market's expectations and forecasters' expectations, which is why they opt for using analyst target price rather than market price when the models are also using analyst forecast.

2.4.2. Applying Reverse-Engineered Models to Identify Mispricing

Previous studies have also utilized the reverse-engineered DCF-models in various ways to identify mispricing. Cogliati et al. (2008) investigate initial public offering (IPO) pricing by measuring growth rates implied in the offer price. The model solves for the implied growth rates of free cash flows over a period of five years, which is the cash flow needed for the implied IPO price. When comparing the ex-ante analyst targets with the ex-post realizations of free cash flows, it was found that the median IPO firm was overvalued at the offering by 74% (Cogliati et al., 2008).

French and Javakhadze (2013) further argue that investors are not only exposed to the quantifiable risk that can be identified through traditional asset pricing models but also “unpriced risk”, which is in all essence mispricing, caused by systematic investor biases which market practitioners are not compensated for. Thus, suggesting that much of the information impounded into stock prices are based on assumptions that are not always rational. The authors identify that most stocks have unpriced risk, rather the question is how large amounts of subjective information the current stock price represents. In the study, a reverse-engineered DCF-model is used to solve for the implied revenue growth that is needed to justify the current stock price. Based on the implied growth rate and the historical distribution, a probability approach is applied to quantify the unpriced risk for a portfolio. Hence, a low probability occurs when the implied revenue growth appears to be far out of reach compared to the firm's historical revenue growth. The authors argue that a larger amount of the information interpreted into the price thereby is subjective and thus not quantifiable by known risk factors. Accordingly, the unpriced risk is higher among “low-probability” stocks, i.e. overvalued stocks, compared to “high-probability” stocks, i.e. undervalued stocks (French & Javakhadze, 2013).

Takács et al. (2019) further develop the reverse DCF-model to identify mispricing in a post-crisis era by investigating 1001 US companies divided by the industry under the period 2010-2017. The authors emphasize that the former reverse DCF-model presented by Cogliati et al. (2008) and the latter by French and Javakhadze (2013) is based on perpetuity assuming continuous growth of cash flows at the growth rate. However, this assumption is rarely realistic, and thus Takács et al. (2019) apply a two-stage model, where growth is only assumed for a finite period, which is then increased by the value of the period thereafter referred to as the terminal value. Further, the authors introduce the concept of "critical cash flow" which is defined as the required cash flow given the current market capitalization. Thus, the “critical cash flow” can be determined by using a reverse DCF-model since the market capitalization, required rate of return, and growth rate are all known variables at any given time. In terms of practical implications, the model aims to identify pricing errors, a concept that is defined as the difference between the “critical cash flow ratio” identified by the model and the actual cash flow ratio being observed. Hence, a positive pricing error refers to an overvaluation of the stock, while a negative pricing error refers to an undervaluation.

Several of the studies also discussed the market's corrections to mispricing. Cogliati et al. (2008) found that there is a negative reaction in the stock performance when cash flows are lower than expected, implying that analysts mispricing due to forecast errors impacts investors' returns. In the study by Takács et al. (2019), the authors conduct further analysis of pricing errors and their relation to market corrections. The result shows that stocks were generally undervalued in the period 2010-2017, since the ex-post cash flow was generally better than expected by investors, consistent among all industries. Further, the market correction mechanism worked with an average correction time of two years and prevented sustained trends of overvaluation or undervaluation. Considering these findings, investors can utilize reverse-engineered valuation models to identify and exploit irrational pricing of equities.

2.5. Contributions to Literature and Hypothesis

To our best knowledge, this is the first reverse RIV-model investigating the market's expectations on ROE. Prior research on the reverse RIV-model has been conducted to determine and improve the valuation estimates on for example the COE or the long-term growth rate (Easton et al., 2002; Nekrasov & Ogneva, 2011). Moreover, the study by Takács et al. (2019) shared our objective to investigate the reasonableness of the market valuation which they have achieved by identifying pricing errors and market corrections. However, our study differs since the model builds on the theory of the RIV rather than the DCF-model, implying that the focus is devoted to ROE instead of cash flows.

There are several advantages of focusing on ROE instead of “critical cash flow”. The foremost reason is that ROE is a more comprehensive measure of a company’s performance as it considers two out of three company statements, namely the income statement and balance sheet, while cash flow only considers the cash flow statement. Furthermore, ROE is a more acclaimed measure in investing spheres. The main differentiating trait is that we will investigate the possibility of creating a ratio that can on an ex-ante, before the fact, determine the reasonableness of market expectations of the future. Accordingly, our study presents a novel application of the reverse RIV-model and a parameter that can be used by investors to identify investment opportunities more efficiently.

Based on our literature review, we have formulated a hypothesis for the first subquestion of our research: Did the market accurately predict the performance of equities between 2011 and 2016? Our hypothesis suggests that the market had inaccurate expectations during this period, as indicated by the previous studies that used reverse-engineered valuation models.

Furthermore, we propose that it is feasible to develop a parameter that can assess the reasonableness of the market's future expectations. This parameter will be instrumental in addressing our second research question: Can we create an accurate *prospective* parameter to evaluate the reasonableness of the market's future expectations?

Table 1: Summary of Previous Reverse-Engineered Valuation Models

Author(s)	Model	Investigates	Assumptions	Main Findings
Easton et al. (2002)	Reverse RIV-model	COE and long-term growth rate	Four year explicit period of analyst forecast	The equity risk premium was higher compared to the result from previous studies
Cogliati et al. (2008)	Reverse DCF-model	Growth rates of free cash flows over a five year period	Constant steady state growth rate at the horizon	The median IPO firm is overvalued at the offering by 74%. Subsequent negative market reactions to post-IPO disclosure of cash flows lower than expected is evident
Nekrasov and Ogneva (2011)	Reverse RIV-model	Fim specific COE and long-term growth in earnings	Four years analyst forecast, testing the model with both unadjusted and adjusted analyst forecasts	The COE measure is significant positively associated with future realized returns (future realized earnings growth)
French and Javakhadze (2013)	Reverse DCF-model	"Unpriced risk" and market returns from "high probability" vs "low probability" portfolios	Two-stage model, where firms enter steady state after year 10	Investing in "high-probability" stocks produces abnormal returns with lower total risk since these firms are more likely to achieve their required revenue growth
Fitzgerald et al. (2013)	Reverse RIV-model	3 012 possible combinations of COE, long-term ROE, and long-term growth	Analyst target price and EPS expectations, ten year explicit period then firms are assumed to enter steady state	The estimates of the equity risk premium is 5,3% which is substantially higher compared to earlier estimates
Takács et al. (2019)	Reverse DCF-model	Required growth in "critical cash flows" and identifying mispricing in a post crisis era	Two-stage model, where growth is only assumed for a finite period	Stocks were generally undervalued in the period 2010-2017, the ex-post cash flow was better than expected by investors, consistent among all industries

Notes: Table 1 summarizes the reverse-engineered valuation models from the literature review, published during the years 2002-2019. The table also specifies the authors, the model applied, what each model investigates, important assumptions, and the main findings.

3. Theoretical Framework

Chapter 3 presents the concept of the RIV-model and its current application by market practitioners. Further, the arguments for choosing the RIV-model and more specifically ROE as the selected output is presented.

3.1. The Concept of the RIV-Model

The RIV-model states that the market value of the firm's equity equals its book value plus the present value of its expected future residual income. Hence, the residual income during the explicit period can be defined as ROE less the equity charge. A common approach is to divide the RIV-model into two stages, where the second term in the expression is the terminal value. The terminal value is the estimated value of an asset projected at a future point when the firm is expected to enter a steady state and can be a substantial part of the intrinsic value (Ohlson & Zhan, 1999). Consequently, the accuracy of the terminal value calculation thereby significantly affects the overall accuracy. Two characteristics should be fulfilled for a company to be in steady state. Firstly, the company should grow at a constant rate by reinvesting a constant proportion of its operating profits into the business each year. Secondly, the company should earn a constant rate of return on both existing capital and new capital invested. In practice, analysts tend to assume that a company enters steady state after 10 to 15 years, but adjustments are made on a company basis (Koller, Goedhart & Wessels, 2005). The model can be specified as the following, where the first term is the discounting of the explicit period and the second term is the terminal value.

Equation 1: RIV-model

$$v_0 = BE_0 + \sum_{t=1}^{N}\left(\frac{(ROE - rE)\ x\ BE_{t-1}}{(1+rE)^t}\right) + \left(\frac{(ROE - rE)\ x\ BE_{N-1}}{rE - gSS}\right)$$

- v_0 = Value year 0, time of applying the model
- BE_0 = Book value of equity year 0
- ROE = Return on equity
- r_E = Cost of equity
- BE_t = Book value at time t
- t = Time as full year period
- N = End of explicit period
- gSS = Growth rate in steady state

The method is applied by market practitioners to determine the intrinsic value of a company or stock, which can then be compared to its current market price to determine whether it is undervalued, overvalued, or at fair value.

3.2. Arguments for the Relevance of the RIV-Model and ROE

The RIV-model allows for the examination of ROE, which is defined as the net income divided by the opening value of owners' equity (Berk & DeMarzo, 2017). ROE thereby combines the income statement i.e. net income with the balance sheet i.e. equity. The ratio is also perceived as the primary financial measure and is a fundamental component in the esteemed "DuPont" system, which summarizes profitability, operating and financing ratios

(Penman, 1991). Accordingly, ROE is conceptually strong and well-known by investors, implying that the relevance of the analysis increases.

The characteristics of ROE have also been explored extensively, and the results from several studies indicate that historical ROE is useful to predict future changes in earnings. Moreover, the current levels of ROE have indicative power of future ROE levels (Penman, 1991; Freeman, Ohlson & Penman, 1982). Further, a large number of studies have quantified that ROE tends to revert to the mean over time. In addition, Fama and French (2000) identify that the further away ROE is from the mean in any direction, the faster the mean reversion occurs. These characteristics make ROE suitable for comparing companies' performance over time and especially investigating averages.

4. Method

This chapter will start with a brief introduction to the reverse RIV-model. The model inputs and the assumptions are then presented to the reader. Thereafter follows a more detailed description of how the model has been operationalized. The chapter will be concluded with a presentation of the accuracy parameter (AP) and reasonableness parameter (RP), where the former is used to evaluate the accuracy of the model output, and the latter is used to identify the reasonableness of the market expectations.

4.1. Model Specification

This thesis applies the RIV-model presented above and the concept of reverse engineering to solve for the implied ROE needed to justify the stock price at the valuation date, similar to how an internal rate of return model (IRR) works. In order to solve for the implied ROE it needs to be the only unknown variable, meaning the other variables in the expression are known. The calculations and assumptions for the other variables besides ROE are presented below.

Note that due to this being an academic study that has studied up to 250 companies over ten industries and five years yielding over 1 500 data rows (companies - years), we have adopted a more relaxed approach than an investor should do when analyzing an individual company or industry with the model. An investor should have a less standardized practice and more firm endogenous assumptions regarding for example the pay-out ratio as well as the other assumptions stated below, in order to yield the most accurate results of the model.

4.2. Calculations and Assumptions of Variables Besides ROE

4.2.1. Cost of Equity

In our model, the cost of equity is applied as the discount rate. To determine the firm-specific cost of equity, we apply the CAPM formula which was introduced by Sharpe (1964) and Lintner (1965). The formula is one of the most frequently used in the market, therefore we argue that CAPM is reasonable to apply when determining the $E(r_E)$ estimates. CAPM outlines the relationship between risk and expected return for a given stock, where the fundamental principle is that investors should be compensated for both the time value of money and the additional risk by investing in the stock. It consists of the risk-free rate (r_f), the company's beta value (β_E), and the expected market risk premium ($E(r_m) - r_f$). We use the U.S.10-year treasury bill as a proxy for the risk-free rate (r_f), since the sample consists of firms from the Standard & Poor’s (S&P) 500 index. This is also the return an investor can receive from a risk-free investment. The additional risk investors take on is displayed by the remaining part of the expression, where a firm's beta value (βE) is multiplied by the expected market risk premium ($E(r_m) - r_f$). A stock's beta value is thus the systematic risk, which is the volatility in relation to the overall market (Berk & DeMarzo, 2017). The formula is presented in Equation 2.

Equation 2: CAPM formula

$$E(r_E) = r_f + \beta_E \, (E(r_m) - r_f)$$

- $E(r_E)$ = Appropriate discount rate for equity according to CAPM
- r_f = Risk-free rate (U.S. 10-Year treasury yield)
- $E(r_m)$ = Expected return to the market portfolio
- βE = Beta value, i.e. systematic or undiversifiable risk

4.2.2. Terminal Value

The reverse RIV-model requires an assumption as to when the company enters a steady state. The steady state implies that the value driver, i.e. residual income should grow at a constant rate. We have determined the explicit period to be 10 years for all companies supported by Koller et al. (2005) and due to a lack of information on firm or industry-specific steady state assumptions. Thereby, assuming that all companies in the sample, irrespective of their business cycle phase will have entered a steady state by that time.

4.2.3. Terminal Growth Rate

In the perpetuity formula, the cost of capital (r_E) and the growth rate (g) in the terminal value expression is constant forever. Given the fact that the stable growth rate is constant, there are several constraints for how high the terminal growth rate can be. No firm can grow at a rate higher than the growth rate of the economy in the long-term, meaning that the constant growth rate cannot exceed the overall growth rate of the economy (Damodaran, 2012). Thus, based on the GDP growth and the historical average rate of inflation, a reasonable assumption is to apply 3% in the model (Nekrasov & Ogneva, 2011).

4.2.4. Clean Surplus Relation

The clean surplus relation implies that any change in the book value of owners' equity can be explained by net income, dividends or capital contributions (Feltham & Ohlson, 1995). In order to incorporate the clean surplus relation in the model, we calculated the retained earnings percentage relationship to the book value at the time the model was applied. Subsequently, we used this relationship as a proxy for the growth in book value per year for the explicit period, meaning if the retained earnings were 10% of book value we assumed a 10% growth in the book value each subsequent year. Retained earnings were calculated by deducting dividends paid (determined by the average pay-out ratio between 2009 and 2019) from the year's earnings.

4.2.5 Application of the Model

The reverse RIV-model calculates the residual income for each year in the explicit period and the terminal value after the tenth year. It then discounts these values based on CAPM as a discount rate in order to get the present value. The share price was deducted in order to get the net present value, which is the total of the present values minus the cost of the investment; the share price. In order to find the market expectations of ROE through the model we used the goal-seek function in Microsoft Excel (other tools can be used in other programs), which tries different levels of ROE to find where the net present value is zero or in other terms when the price of the equity equals the present value of residual income and the terminal value. In many ways, our model is similar to an IRR model because both try to find where the net present value is zero for the factor of the value expression (RIV or DCF). The main difference is that our model finds the required ROE while IRR finds the required rE.

4.3. Creation of Accuracy Parameter and Reasonableness Parameter

In order to investigate if our model can be used to determine the reasonableness of the market's expectations of ROE, we have constructed two parameters. AP considers the model in relation to the observed performance after the valuation date and is a proxy for the accuracy of the market's expectations. RP considers the observed performance available at the valuation date and is a proxy for the reasonableness of the expectations.

4.3.1. Accuracy Parameter

In order to observe if the market has accurate expectations we use a similar definition as Takács et al. (2019) used for “mispricing”. The authors calculated mispricing by subtracting the observed cash flow one year after the application of the model from the estimates of “critical cash flow”, suggesting that when the difference is equal to zero the market is completely rational or accurate in its estimate[1]. Our parameter uses a similar expression with the difference being the length of the period as we look at three-year averages instead of just one year. The rationale for looking at a three-year average of ex-post ROE instead of only one year as done by Takács et al. (2019), is that year-specific fluctuations can be avoided. This will yield how accurate the market expectations were in relation to what actually happened. One clear limitation of comparing a model estimate with data points after the fact is the so-called “surprise news” (Easton & Monahan, 2005), i.e. information about the earnings and discount rate after the fact, which of course should affect the valuation of the company. However, it is not possible to get away from this conundrum because investing

[1] In this text we use the markets accuracy, reasonableness and valuation synonymous as they can all explain inefficiency and irrationality of the markets, because an inaccurate market is also unreasonable and has not a correct valuation.

judgments will always be made on an ex-ante basis (before the fact), thus dealing with probabilities and not certainties. Figure 1 illustrates how the parameter works on a timeline and its mathematical expression.

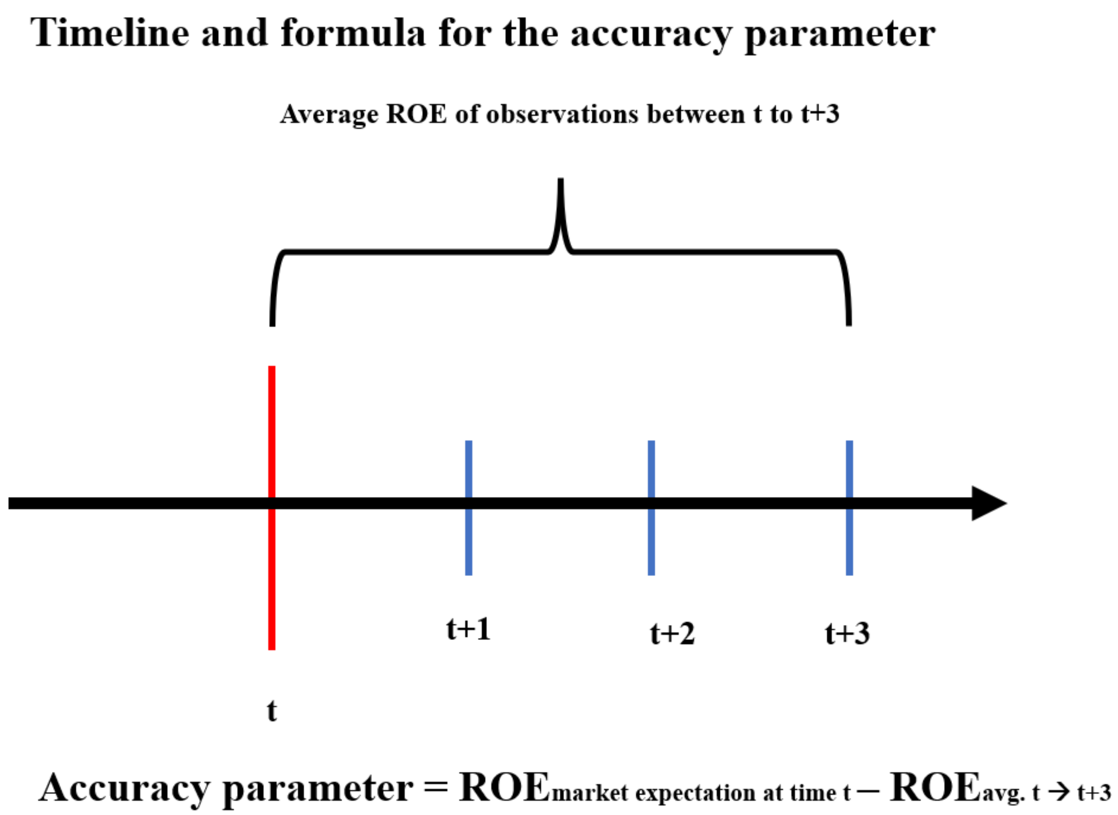
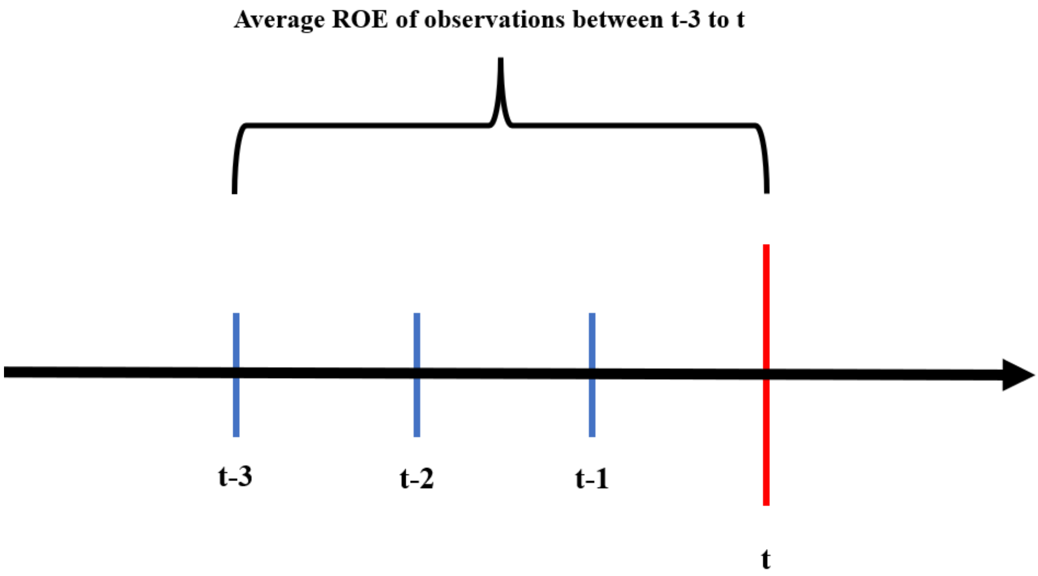


Figure 1: Illustrates on a timeline where AP takes data from. Also, presents the equation used to calculate AP, which is the average observed ROE between the years t to t+3 subtracted from the market expectation at time t according to the model.

4.3.2. Reasonableness Parameter

In order for market expectations to be relevant for investors or researchers it has to give actionable information. The logical choice is to put the expectations in relation to what is known and observable at the time of analysis, which is the historical ROE. A parameter is therefore created that examines the difference between the market expectations and the three-year average historical performance. Using historical data from the preceding three years decreases the risk of applying outdated values of ROE that no longer are a good representation of the firm's current and future ROE. The mathematical expression and illustration RP can be seen below in Figure 2:

Timeline and formula for the reasonableness parameter



$$\textbf{Reasonableness parameter} = \mathrm{ROE}_{\text{market expectation at time } t} - \mathrm{ROE}_{\text{avg. } t\text{-}3 \rightarrow t}$$

Figure 2: Illustrates on a timeline where RP takes data from. Also, presents the equation used to calculate RP, which is the average observed ROE between the years t-3 to t subtracted from the market expectation at time t according to the model.

If RP is greater than zero, we consider market expectations unreasonable; if it is equal to or below zero, we deem them reasonable. We expect this to be true in general, albeit for some firms it is not unreasonable for the market to have higher return expectations than the company's previous performance due to firm-specific benign circumstances. However, the opposite might be true as well. Thus, the reasonableness parameter should not be the sole criterion for analyzing or making judgments on equity valuation, but a part of a myriad of information investors consider when making the appreciation of the appropriate value of the equity.

4.4 Measurement Variable for Presenting Changes in AP and RP

The result of changes in the value of AP and RP will be presented in basis points (BP) which is a commonly used unit of measurement in the field of finance. It describes the rate of change in the value of for example a stock or index. One BP equals 0,01% and by using BP instead of percentage, the ambiguity with regards to if the change is absolute or relative is eliminated (Investopedia, 2022).

5. Data Collection

The data collection chapter gives the reader an overview of the sample studied. The sample selection is presented and the basis for the exclusion of data, followed by information about the data gathering.

5.1. Sample Selection and Exclusion of Data

We have applied the model and gathered data from companies in the following S&P industry indexes.

- S&P Health Care Select Sector (XLV)
- S&P Consumer Discretionary Select Sector (XLY)
- S&P Consumer Staples Select Sector (XLP)
- S&P Energy Select Sector (XLE)
- S&P Financial Select Sector (XLF)
- S&P Industrial Select Sector (XLI)
- S&P Materials Select Sector (XLB)
- S&P Real Estate Select Sector (XLRE)
- S&P Technology Select Sector (XLK)
- S&P Utilities Select Sector (XLU)

The analysis is conducted on the index constituents from 2011 to 2016. The period was selected in order to limit the effect of the financial crisis in 2008 and the COVID-19 pandemic in 2020. The selected period pertains to RP which will use data from 2009, three years prior to the initial application, and AP which incorporates data from 2019, three years after the last application of the model.

The potential sample size for our six years study period is 3 000 company-years because S&P 500 index has, as the name suggests, 500 constituents at each given time. However, about half of the constituents of S&P 500 companies needed to be excluded each year because of either lack of sufficient data; beta values, earnings data, or share price. In addition, companies with negative ROE on the year applying the model were also excluded since the model requires positive implicit ROE to be informative. Some companies also yielded extreme RP and AP figures due to extreme variance in ROE in the sample period due to perhaps changes in accounting standards or merger and acquisition activities. These observations were also ousted from the final sample. Moreover, the whole S&P Communication Services Select Sector (XLC) was excluded due to the low count of applicable companies, the highest number being six companies. The final sample can be found in Appendix 1 and Appendix 3.

5.2. Gathering of Data for the Model

The accounting data; earnings, book value, and pay-out ratio, are gathered from S&P Capital IQ on a full-year basis. The stock price information is also gathered from Capital IQ based on the original filing date of the full-year report in order for the report information to be reflected in the share price. The company's beta value in the CAPM formula is gathered from the Wharton Research Data Service Beta Suite dataset on the month of the original filing of the full-year report. The risk-free rate is based on the US 10-year Treasury yield based on the month of the original filing date. We chose an expected market return of 9% used in the CAPM formula (Berk & DeMarzo, 2017). This entailed a market risk premium, the premium attributed to equity holders for taking risk, landed between the interval of 5,2% to 8,6% during the period which is close to the historical range (Chabi-Yo & Loudis, 2020).

6. Empirical Results

In our study we have applied our model in two different timespans, the first analyzing market expectations between 2011 to 2016, and the second for 2022. This chapter presents the results from both studies starting with a descriptive analysis of ROE, AP, and RP for the first timespan. Further, the aggregated data of the accuracy of the market's expectation, i.e., the average AP for the sample and each respective industry will be presented. Thereafter, the correlation between RP and AP is shown. Lastly, the result from the 2022 study is presented.

6.1. Original Study Conducted Between the Years 2011 to 2016

In the first study there were 1 437 observations, company-years, divided between ten industries and six years. Disclosure of the tickers for all companies and years is presented in Appendix 1. Due to the limitations of data from S&P, the following results will be based on equal weights of the constituents, though they have different weights in the S&P 500 index.

There was a significant difference between the years with regards to for example max of model estimates of ROE and standard deviation. In 2011, the lowest max estimate of ROE and also the lowest standard deviation of ROE were observed. Moreover, observing the max values for ROE estimates, 2011 had by far the lowest estimate at 101,5%, while the highest estimate is in 2015 at 227% (Appendix 2). However, the average model estimate of ROE does not diverge significantly between the years, albeit a gain in estimates from 2011 to 2014 and then a slight decrease. Furthermore, the average ROE between industries exhibited a range from 7,3% for Utilities to 26,7% for Real Estate.

Average of model estimates for ROE, in percent

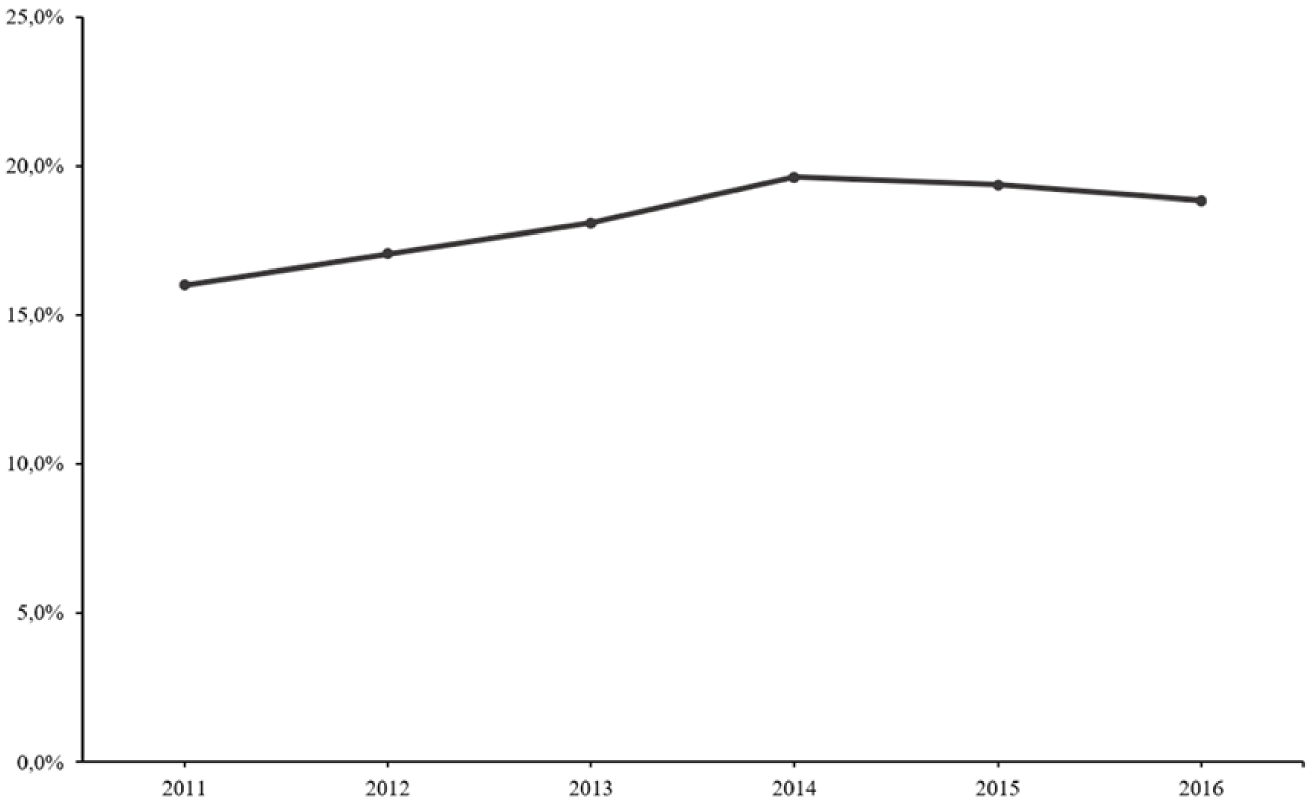


Figure 3: The graph shows the average model estimates for ROE, i.e. the average implied ROE for the total sample between the years 2011 and 2016. The model estimates of ROE have been calculated for each company in the sample through the reverse-engineered RIV-model.

Average of market estimates according to the model per industry between the years 2011 to 2016, in basis points

Industries	Consumer discretionary	Consumer staple	Energy	Financials	Health care	Industrial	Info tech	Materials	Real estate	Utilities	Average all years
2011	19,0%	10,9%	12,5%	14,2%	11,0%	17,8%	23,0%	18,4%	21,1%	7,0%	16,0%
2012	23,2%	10,1%	12,6%	14,6%	11,2%	19,9%	22,8%	17,4%	26,5%	7,5%	17,1%
2013	24,0%	10,1%	13,1%	16,1%	23,9%	22,4%	22,6%	17,9%	23,2%	8,6%	18,1%
2014	25,0%	11,4%	13,8%	18,1%	24,6%	20,8%	27,6%	19,3%	27,7%	6,7%	19,6%
2015	26,8%	12,8%	13,8%	17,5%	17,3%	18,1%	26,3%	16,1%	29,8%	6,7%	19,4%
2016	22,9%	13,4%	15,5%	12,3%	15,1%	20,6%	26,9%	21,4%	27,8%	7,4%	18,8%
Average all years	**23,6%**	**11,5%**	**13,5%**	**15,7%**	**17,5%**	**20,0%**	**24,9%**	**18,4%**	**26,7%**	**7,3%**	**18,2%**

Table 2: Reports the average market estimates of ROE per industry for each year respectively and for all years (2011-2016). In addition, it displays the average market estimates of ROE for the total sample for each year respectively and for all years (2011-2016).

6.1.1. Aggregate Data of Pricing Error

The first subsection of our research question is: Did the market have accurate expectations of equities performance between the years 2011 to 2016? Since AP is the delta between the market estimates of ROE and the actual ROE observed three years after the estimation date, it encloses the market error of expectations of ROE. As previously mentioned this is a similar definition Takács et al. (2019) had for its calculation of mispricing. Thus, we have formulated the following hypothesis test to see if the market's expectations are accurate or not.

H_0: AP = 0

H_1: AP $\neq$ 0

Average of AP between the years 2011 to 2016, in basis points

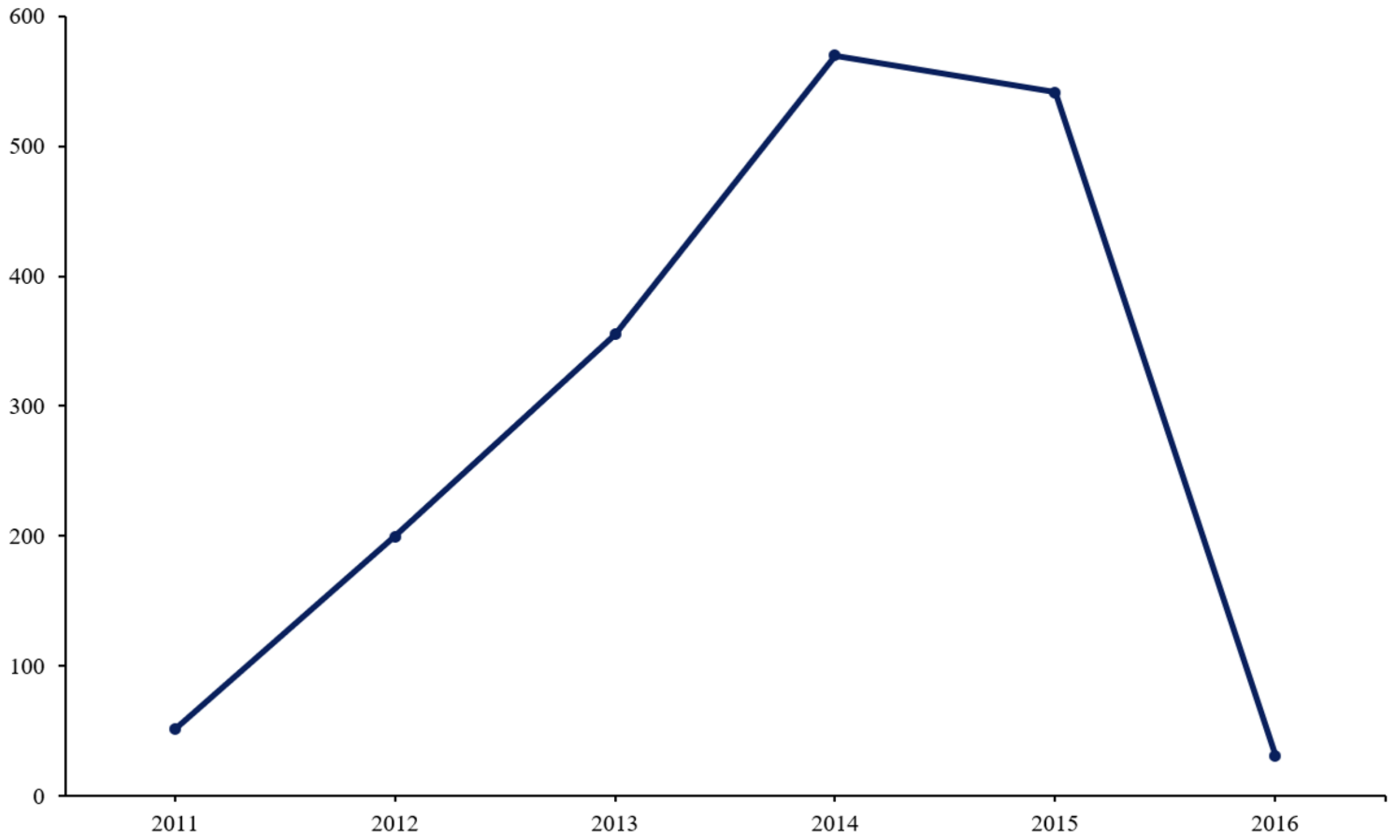


Figure 4: Shows the average AP for the total sample between the years 2011 to 2016. AP has been calculated by deducting the three-year average of ex-post observations of ROE from the market's implied estimates of ROE, which has been obtained from the reverse RIV-model.

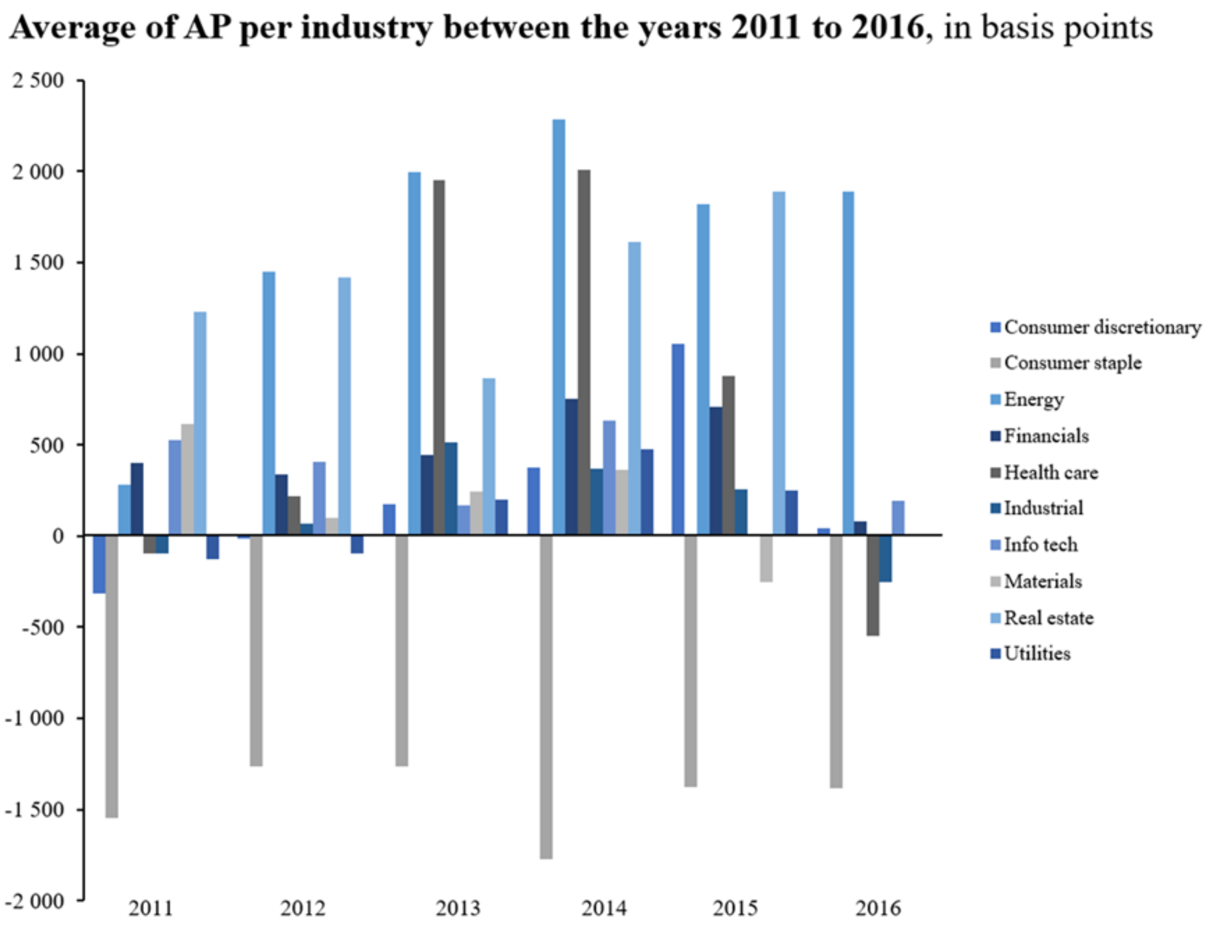


Figure 5: The columns show the average AP per industry between the years 2011 to 2016. The included industries are Consumer Discretionary, Consumer Staple, Energy, Financials, Health Care, Industrial, Info Tech, Materials, Real Estate and Utilities.

Average of AP per industry between the years 2011 to 2016, in basis points.

Industry	**Consumer discretionary**	**Consumer staple**	**Energy**	**Financials**	**Health care**	**Industrial**	**Info tech**	**Materials**	**Real estate**	**Utilities**	**Average all years**
2011	-317	-1 548	283	398	-96	-95	526	616	1 232	-126	51
2012	-17	-1 262	1 448	341	218	65	408	102	1 417	-98	200
2013	175	-1 262	1 996	447	1 950	515	170	243	863	202	355
2014	373	-1 770	2 285	750	2 010	372	635	363	1 615	473	570
2015	1 054	-1 380	1 819	708	879	255	11	-251	1 891	250	541
2016	43	-1 384	1 889	83	-545	-252	196	0	0	0	31
Average AP/ *AP standard deviation in %*	**233**/*36%*	**-1 440**/*19%*	**1 627**/*18%*	**485**/*11%*	**679**/*24%*	**118**/*16%*	**330**/*21%*	**185**/*25%*	**1 066**/*18%*	**116**/*14%*	**299**/*24%*

Table 3: Reports the average of AP per indsutry for each year respectivly, as well as the average AP for the whole sample per year. The final row reports the average AP and the standard deviation in percentage for the whole sample period.

The aggregated data shows that AP was significantly higher than 0 for all years with an average of 299 basis points (BP), indicating the market was optimistic in its estimates. However, there were some divergences between industries where Consumer Staple was the only industry with an average negative AP at -1 440 BP and Energy had the highest average AP at 1 627 BP. Both the Consumer Staple and Energy sector had a standard deviation below the average standard deviation for the sample. Moreover, the result also shows that the

Materials, Real Estate and Utilities sectors had an AP of 0 during 2016. Thus, the data is to some small extent ambiguous as to whether the market had accurate expectations or not. However, the aggregated data distinctly prove that the market estimates do not equal 0, therefore the null hypothesis can be rejected.

Worth noting is that AP cannot be interpreted as an exact estimation for overvaluation or undervaluation in terms of price, since the price is not considered when calculating AP. However, AP can be used to observe the relative valuation, meaning an AP value of 500 BP is considered more overvalued than an AP value of 100 BP. The relative overvaluation increased consistently between 2011 to 2014 but had a significant correction between 2015 and 2016, as AP went from 541 BP in 2015 to 31 BP in 2016, which also is the lowest observation at the aggregated level.

6.1.2. Predictive Information RP

Proving that RP is a relevant parameter to determine the reasonableness of the expectations on an ex-ante basis, is not as clear-cut as investigating the accuracy of market expectations after the fact. However, if considering AP a proxy for the accuracy of market expectations, the correlation between dito and RP can be used to determine the correlation between *proven* accuracy, i.e. AP and *predictive* accuracy, i.e. RP. If the correlation is significant, which we determine to be at a 5% significance level in accordance with praxis in academia (Aidley, 2018), the relationship is considered strong enough to infer that RP has relevant *predictive* information on the reasonableness of the market's expectations. Accordingly, the hypothesis test is formulated as follows:

H_0: corr(AP, RP) = insignificant
H_1: corr(AP, RP) = significant

To test the hypothesis, a two-tailed Pearson bivariate correlation test[2] is performed. The results conclude that there is a significant correlation of 74,2% for the total sample between AP and RP. Moreover, as observable the correlation ranges between 46,0% for Utilities to 91,6% for Real Estate, albeit, all industries had significant correlation. Thus, the null

[2] Pearson correlation measures linear relationship strength between two continuous variables in percentage, with -100% indicating perfect negative correlation and 100% indicating perfect positive correlation.

hypothesis can be rejected which indicates that RP is an ex-ante parameter that contains *predictive* information of the market's reasonableness.

Table 4: Correlation table for AP and RP

Industry	Number of observations	Significance	Correlation
Consumer discretionary	284	<0,01	73,8%
Consumer staple	131	<0,01	85,4%
Energy	128	<0,01	51,8%
Financials	270	<0,01	91,5%
Health care	36	<0,01	79,6%
Industrial	64	<0,01	62,8%
Info tech	220	<0,01	77,6%
Materials	96	<0,01	54,7%
Real estate	70	<0,01	91,6%
Utilities	138	<0,01	46,0%
Total	**1437**	**<0,01**	**74,2%**

Table 4: Reports the number of observations, the significance level and the correlation coefficient from a two-tailed bivariate correlation test between AP and RP. The numbers are presented per industry and for the total sample.

Oculary a comparison between AP and RP on a graph shows a strong resemblance between RP and AP, as both AP and RP had a similar increase in the early years and a significant correction between 2015 and 2016. The average AP for the sample was 299 BP compared to 305 BP for RP. Contrary to the result from AP, no industry had 0 BP for RP, albeit the Industrial sector had RP closest to 0 with RP of 96 BP. Moreover, Consumer Staple has by far the lowest RP, consistent with the result for the AP. As to the highest observations, the Real Estate sector had the highest RP of 1 281 BP. These outliers compared to the other industries both had a standard deviation below the average for the whole sample, as the outliers for AP also did.

Average of RP between the years 2011 to 2016, in basis points

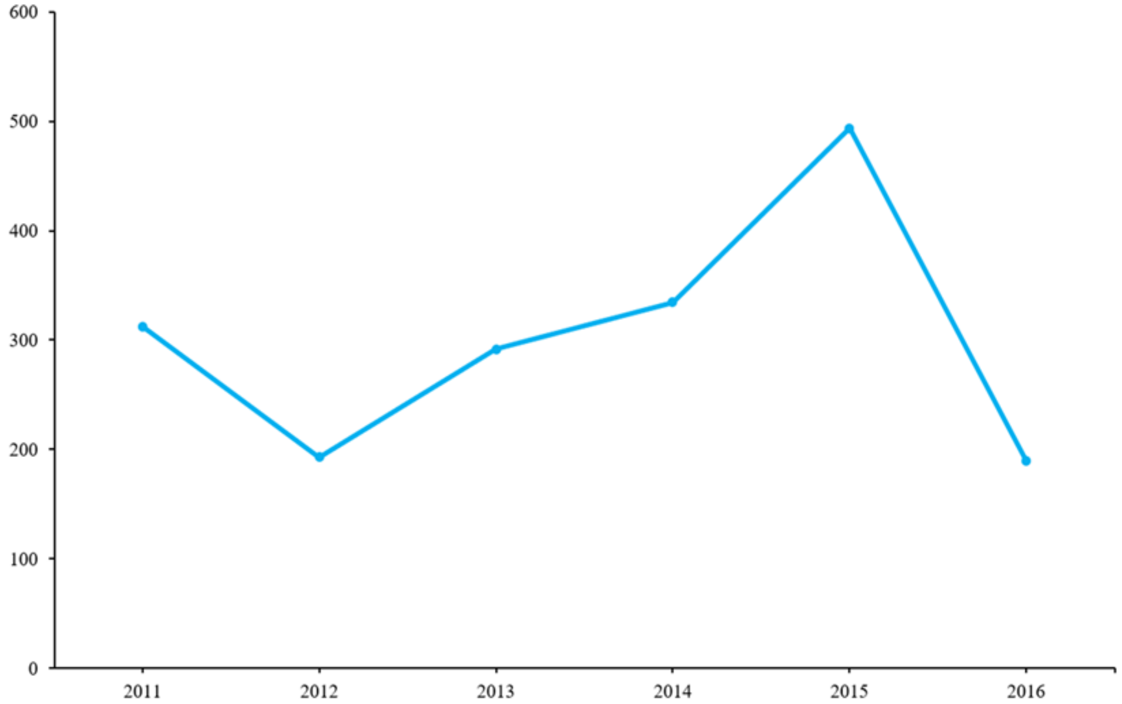


Figure 6: The graph shows the average of RP for the total sample between the years 2011 to 2016.

Average of AP and RP between the years 2011 to 2016, in basis points

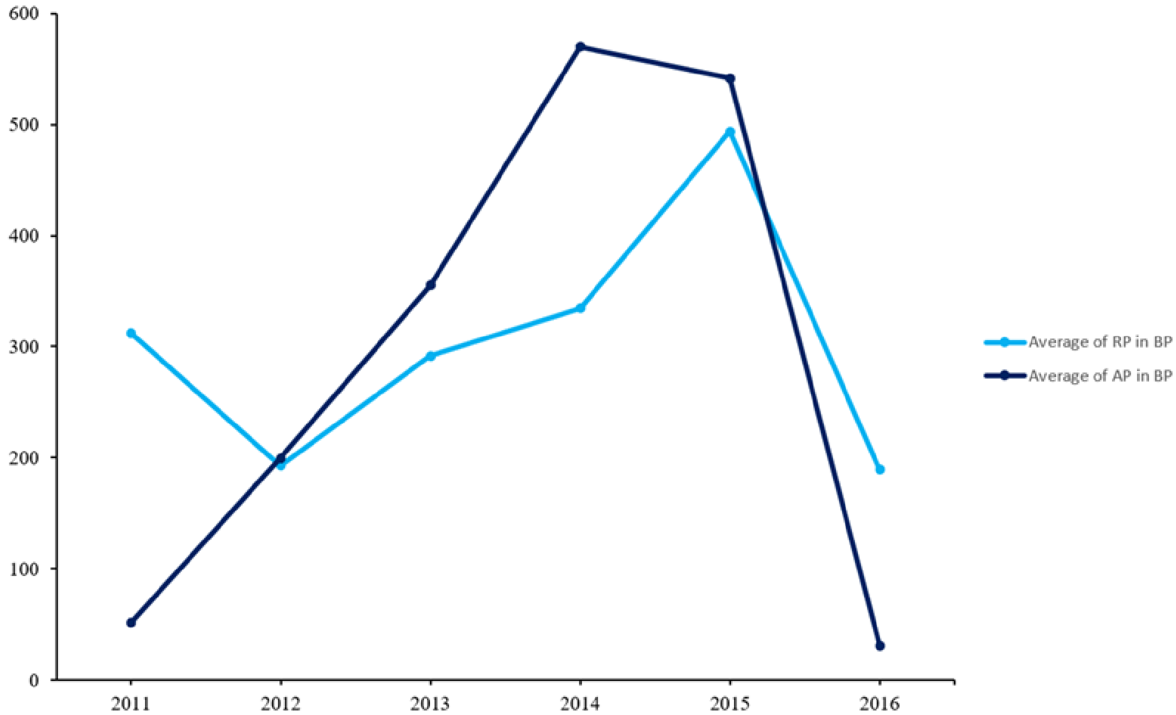


Figure 7: The graph illustrates the average of AP and RP for the total sample between the years 2011 to 2016.

Average of RP per industry between the years 2011 to 2016, in basis points

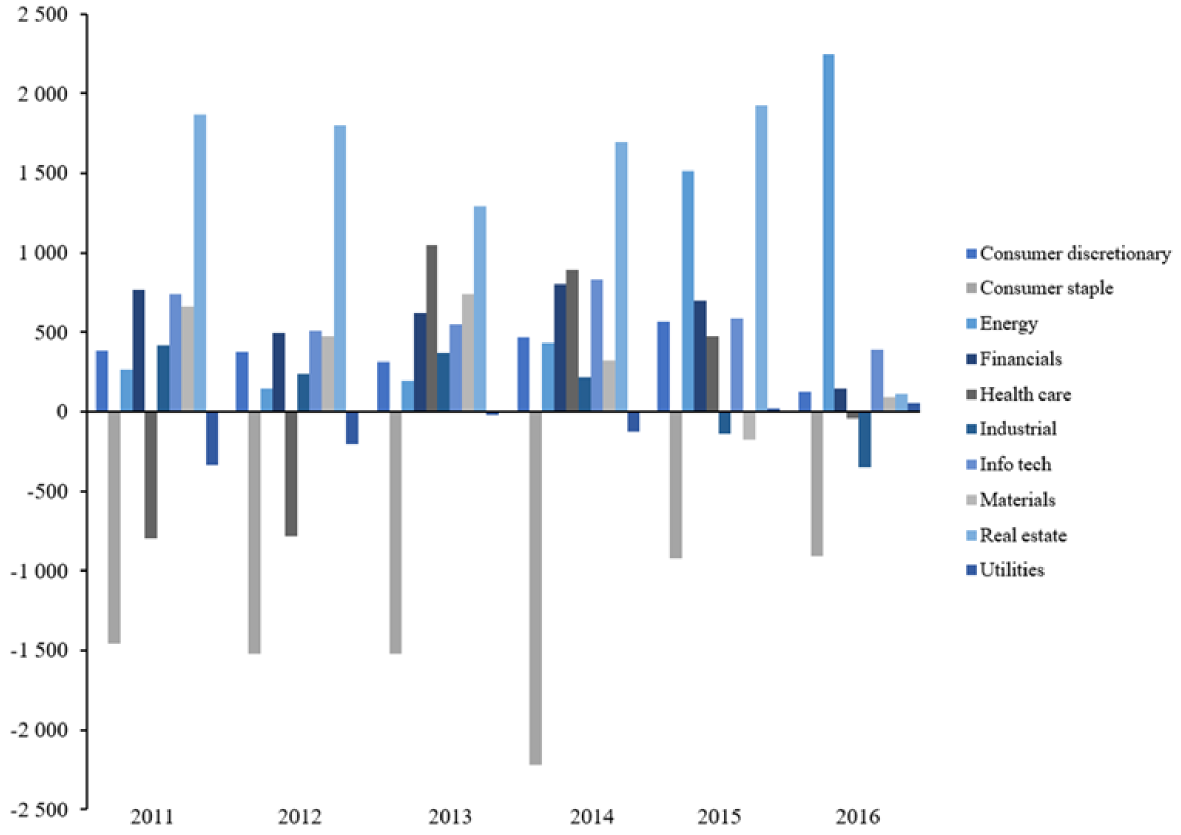


Figure 8: The columns illustrate the average of RP per industry between the years 2011 to 2016. The included industries are Consumer Discretionary, Consumer Staple, Energy, Financials, Health Care, Industrial, Info Tech, Materials, Real Estate and Utilities.

Average of RP per industry between the years 2011 to 2016, in basis points.

Industry	**Consumer discretionary**	**Consumer staple**	**Energy**	**Financials**	**Health care**	**Industrial**	**Info tech**	**Materials**	**Real estate**	**Utilities**	**Average all years**
2011	384	-1 460	262	769	-794	421	742	665	1 871	-338	312
2012	376	-1 520	145	493	-781	237	506	476	1 799	-200	193
2013	314	-1 520	193	618	1 050	369	555	742	1 289	-22	292
2014	470	-2 223	433	803	895	214	832	322	1 697	-126	334
2015	562	-923	1 517	699	476	-138	589	-174	1 925	20	494
2016	126	-908	2 250	145	-41	-350	391	89	109	54	189
Average RP/ *RP standard deviation in %*	**374**/*34%*	**-1 432**/*22%*	**756**/*18%*	**611**/*11%*	**215**/*19%*	**96**/*12%*	**603**/*21%*	**367**/*23%*	**1 281**/*18%*	**-100**/*11%*	**305**/*23%*

Table 5: Reports the average of RP per indsutry for each year respectivly, as well as the average RP for the whole sample per year. The final row reports the average RP and the standard deviation in percentage for the whole sample period.

6.2. Analysis of Current Market Expectations Through a 2022 Study

Having now established that RP contains *predictive* information of the market's expectations, it is possible to analyze the current market expectations based on the latest S&P 500 constituents with financial figures from the latest fillings, i.e. the 2022 full year report. From this, RP can be calculated and the current reasonableness of the market expectations can be derived. In order to conduct the study, some slight adjustments to the original methodology have to be made due to limitations in the availability of the data. The company beta data from Wharton Research Data Service Beta Suite is only available until December 2022. Therefore an altercation with our original model had to be made concerning the CAPM calculation. When calculating CAPM in the study between 2011 to 2016, the model used monthly beta and risk-free rate data as of the month of the original filing of the full-year report. However, since many of the companies in the study had their original filing after December 2022, the beta value and risk-free rate used in the CAPM formula were the last available data from the data sources, i.e. December 2022.

The final sample ended with 366 companies, ranging from 18 in the Energy sector to 58 in the Financial sector. Meaning that 26,8%, or 134 observations from the total 500 potential observations needed to be excluded, the exclusion was made on the same basis as the original study. The sample tickers are provided in Appendix 3.

Average RP per industry in 2022 study, in basis points

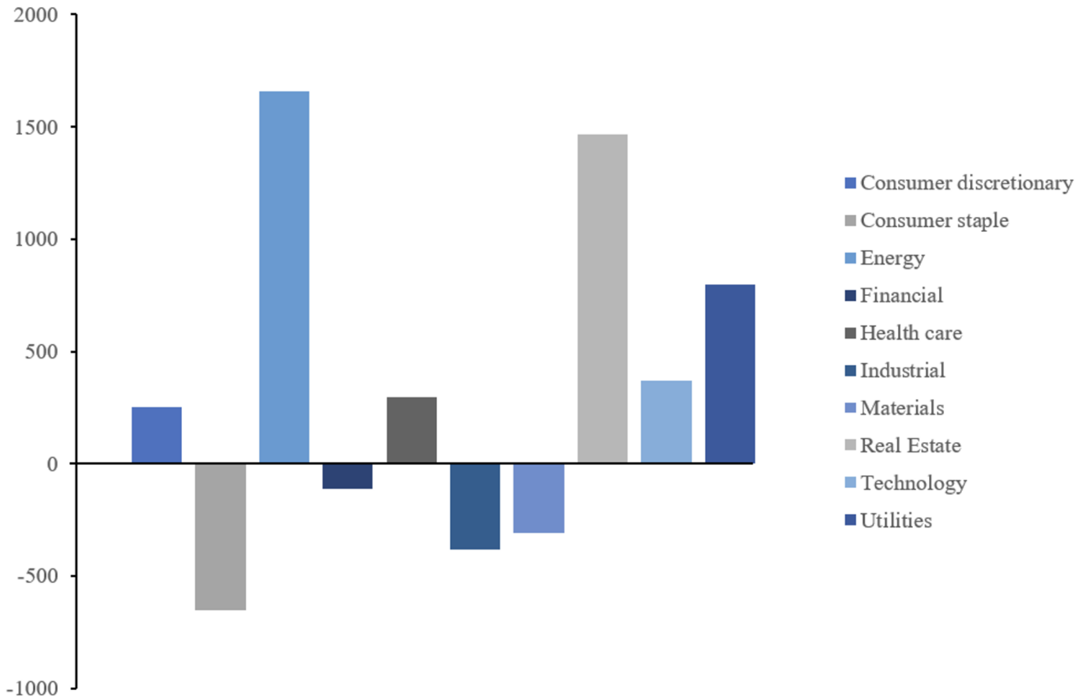


Figure 9: The columns illustrate the average RP per industry in 2022. The included industries are Consumer discretionary, Consumer staple, Energy, Financials, Health care, Industrial, Info tech, Materials, Real estate and Utilities.

Summary statistics of 2022 study

Industries	Consumer discretionary	Consumer staple	Energy	Financial	Health care	Industrial	Materials	Real Estate	Technology	Utilities	S&P 500
Average ROE according to model	22,2%	15,4%	13,5%	14,6%	17,6%	20,0%	16,0%	24,2%	23,6%	13,1%	**18,3%**
Average of RP in basis points	253	-651	1660	-112	295	-383	-308	1466	368	797	**188**
Number of observations	37	28	18	58	49	59	22	21	48	26	**366**

Table 6: Reports summary statistics for the total sample size and per industry for the 2022 study. It included the average estimated ROE, RP and the number of observations.

The average RP was 188 BP compared to 305 BP in the original study from 2011 to 2016, which indicates that the market now has more reasonable expectations. Albeit, the market still has optimistic expectations as RP is positive. Interestingly, the model estimates do not differ significantly between the studies, with 18,2% and 18,3% ROE estimates for the original and 2022 study respectively. This indicates that the market expects companies to perform slightly better in terms of ROE in later years.

With regards to the industry-specific insights Consumer Staple still has the lowest RP at -651 BP, although it has substantially increased from -1 432 BP in the original study. The Financial, Industrial and Materials sector also have a negative RP, which is a significant difference from the original study. The Energy sector had the highest relative valuation at an RP of 1 660 BP in 2022 and also the highest *proven* overvaluation in the original study, with the highest AP in four out of six years.

7. Discussion of Results and Limitations

Entering the discussion on whether markets are efficient or not is always a difficult and paradoxical feat. Most models, including ours, rely on EMH in that it assumes that the market price equals the fundamental value of the equity. In order to investigate the efficiency of markets its underlying assumption needs to be adopted. However, as several previous studies have shown, the market tends to be inaccurate in its estimates (Takács et al., 2019). The inaccuracy can, according to behavioral finance, stem from the fact that other speculative components such as cognitive biases are incorporated into the share price (DeBondt & Thaler, 1987). Overconfidence is one example that suggests that investors tend to overestimate their forecast and valuation skills (Daniel et al., 1998). Furthermore, the limits to arbitrage also suggest difficulties for rational investors to reverse the deviation in stock prices caused by less rational investors (Shleifer & Vishny, 1997). Accordingly, we were not surprised to find that the market was on average inaccurate in estimates. The observations in 2016 for Materials, Real Estate and Utilities with an AP of 0 can be seen as exceptions to the notion that the market is inefficient.

Since the price is the market's calibrating tool[3] to adjust its estimations, one could infer that inaccuracy in reality also is a form of mispricing as Takács et al. (2019) argue, and subsequently is an inefficiency. We think this is a valid logic, however, one could also argue that the market should be awarded some degrees of freedom in its prediction, due to for example the existence of "surprise news" as Easton and Monahan (2005) mentions. In addition, proponents of the rationality of the market would also point to the fact that the S&P 500 increased 75,2%, or a 9,9% compound annual growth rate between 2011 to 2016 (S&P 500, 2023), at the same time when the AP was consistently above 0 BP. Accordingly, posing a paradox as AP would rather indicate a price decrease that would calibrate the estimations to a more accurate level. These are valid objections to the notion of mispricing, but we would argue that AP and RP can be used as indications of *proven* and *predictive* overvaluation and undervaluation. The market can't consistently have unreasonable or over-optimistic expectations since the market will eventually correct itself. Furthermore, the sample period was explicitly chosen to avoid the market crashes of 2008 and 2020, meaning the whole market cycle of booms and busts was not analyzed, only the beginning boom period. Moreover, the observed downturn in AP between 2015 and 2016 to a clearly more reasonable level of AP, coincided with two minor market downturns in 2015 (Investopedia, 2021) indicating that the market needed to correct its over-optimism. Lastly, when analyzing the latest financial figures available, which incorporated figures from the crash of 2020 and its fallout in the figures for 2021 and 2022, a substantial decrease of RP compared to the original study was observed.

Noteworthy is that the implications of mispricing differ from our foremost reference study, Takács et al. (2019), which ascertained an undervaluation of the market for almost the same period (the years 2010 to 2017 compared to our sample period between 2011 to 2016). The three main notable differences between our studies are firstly the company sample, as they focused on a larger sample size, and the model used to extract the market expectations. Secondly, they had a shorter frame for calculating mispricing, with only one year ahead which implies a higher risk for year-specific fluctuations. Thirdly, we did not have the exact same assumption of the discount rate, etc, which clearly affects the results, and our inferences are therefore contingent on our assumption. However, well-founded as we argued in the

[3] The price is a calibration tool for the market because when the price is decreased so are the required expectations of the operational parameter, like ROE, *ceteris paribus*.

method section. We see this as a limitation of equity valuation models as a whole because they are entirely contingent on the assumptions made. The notion of a fundamental or intrinsic value can only exist on a theoretical level, as when applying a model to a real situation the noise and inconsistency of the world is uncovered. However, because reverse models remove the need for forecasting one level of complexity and room for error is removed, which should yield more accurate estimations.

The results would also indicate a significant difference in valuation between industries. Consumer Staple, consisting of companies like Procter & Gamble and the Coca-Cola Company, is indicated to be undervalued by RP and is *proven* to be undervalued by AP during 2011 to 2016. Additionally, Consumer Staple is currently the most undervalued industry based on the result of the 2022 study. Moreover, the industry also has a high correlation between RP and AP, indicating that the current RP figures are reliable. Therefore our study indicates that Consumer Staple is an unpopular industry in the market, which is further accentuated by the price performance of the sector over the previous 10 years (Figure 10). The sector has only increased 84%, which is not a substantial gain compared to the Consumer Discretionary sector with an increase of 131%. Moreover, the industry constantly had a standard deviation below the average for the whole sample, which speaks to the notion that it's the industry that is unpopular in the market and not just pulled down by individual outlier constituents. A practical implication for a *value investor* from these findings is that the Consumer Staple sector consists of attractive investment opportunities. Moreover, Berkshire Hathaway, Buffett's investment firm, has significant positions in both Procter & Gamble and The Coca-Cola Company which further corroborate our notion of the practical implications (Berkshire Hathaway Inc, 2023).

The price-performance in conjunction with AP and RP indicates that the Energy sector has seen a substantial decrease in operating performance. Price performance over the last 10 years is also the lowest for the Energy sector, while at the same time, it has the highest AP in the original study and the highest RP in the 2022 study. Hence, since the relatively high AP can’t be explained by a relative price increase, we can deduce that relatively poor operational performance in ROE is the cause.

S&P 500 performance over 10-years, April 2013 to January 2023, as an index

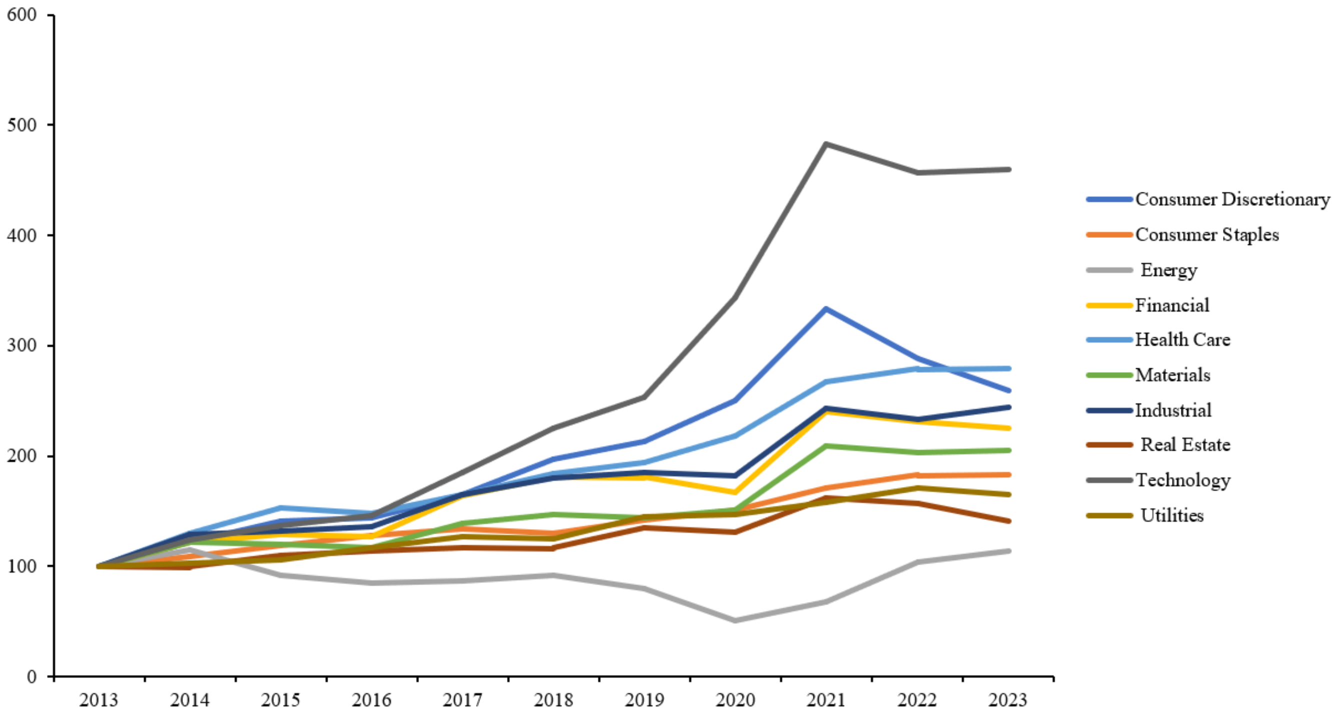


Figure 10: Illustrates the price performance of the S&P 500 index over a 10-year period, from April 2013 to January 2023. The included industries are Consumer Discretionary, Consumer Staple, Energy, Financials, Health Care, Industrial, Info Tech, Materials, Real Estate and Utilities.

Table of S&P 500 performance per industry starting in April 2013 to January 2023, as an index..

Years	Consumer Discretionary	Consumer Staples	Energy	Financial	Health Care	Materials	Industrial	Real Estate	Technology	Utilities
2013	100	100	100	100	100	100	100	100	100	100
2014	122	109	115	121	130	122	129	100	124	102
2015	140	119	92	129	153	120	132	110	137	106
2016	144	128	84	127	148	117	136	114	145	117
2017	165	133	87	164	165	139	165	117	185	127
2018	197	130	92	181	184	147	180	116	225	125
2019	213	141	79	181	194	144	185	135	253	144
2020	250	151	51	167	218	151	182	131	343	147
2021	333	171	68	240	268	209	244	162	483	158
2022	289	183	104	231	279	203	233	157	457	171
2023	259	183	114	225	279	205	244	141	459	165

Table 7: Shows the price performance of the S&P 500 per industry starting from April 2013 to January 2023, and is presented as an index with a starting value of 100

8. Conclusion and Future Research

In this study, we could find support for both our hypotheses. Firstly, the market did not have accurate expectations of the ROE performance for the equities in our sample. Secondly, RP has *predictive* information and is therefore a useful parameter for market participants and managers. Therefore, the answer to this thesis research question; “Can a reverse-engineered model be applied to assess the reasonableness of market prices for investment purposes?”, is affirmative. Through a reverse-engineered RIV-model, we have been able to establish that the market had inaccurate estimates of ROE during all years studied, with three exceptions on the industry level, and we could establish the relevance of the RP which can be used by investors to find and reject investment. These findings can have significant positive practical implications for market participants that choose to adopt our, or similar models, in their effort to find profit in the equity market.

For future research, we have acknowledged several interesting areas. Firstly, we suggest researchers investigate the potential reasons for the difference in conclusion between our study and the study by Takács et al. (2019). The two main reasons for the difference in results are the underlying assumptions and or difference in the underlying valuation model applied, namely the RIV-model and the DCF-model. Secondly, we suggest future research to develop a more refined method for *proving* that the ex-ante parameter has *predictive* information. As this thesis's main contribution and distinguishing trait is to open up the field for finding *prospective* parameters through the use of reverse-engineered valuation models, we believe others will be able to leverage our findings in order to reach higher heights in knowledge.

Appendix

Appendix 1 - S&P 500 constituents used in the original study between 2011 to 2016[4]

https://livehhsse-my.sharepoint.com/:x:/g/personal/50743_student_hhs_se/ETA4jwkVtW9GhB5H2TyXxCgBROkhqgg6q9vRnvqfXIhTPA?e=2nW34T

Summarizing statisitcs original study between 2011 to 2016

Years	Count of Model	Max. of Model	Min. of Model	StdDevp of Model	Max. of AP in BP	Min. of AP in BP	StdDevp of AP	Max. of RP in BP	Min. of RP in BP	StdDevp of RP
2011	224	101,5%	2,9%	11,6%	10144	-7194	17,0%	8745	-7723	18,4%
2012	229	219,5%	0,0%	17,2%	21784	-7384	22,8%	21137	-7372	21,3%
2013	236	196,7%	2,3%	17,0%	19183	-7456	23,3%	19318	-7372	21,6%
2014	255	219,8%	2,3%	18,5%	21055	-9873	27,7%	21975	-11213	24,7%
2015	251	227,0%	0,6%	20,2%	21154	-8429	26,3%	22533	-7580	24,6%
2016	242	144,9%	1,4%	15,9%	12733	-8493	23,5%	14007	-6254	23,4%
Total/average all years	**1437**	**227,0%**	**0,0%**	**17,1%**	**21784**	**-9873**	**23,9%**	**22533**	**-11213**	**22,6%**

Appendix 2: Shows statistics that aim to describe the overall findings of the study conducted based on study conducted on the years 2011 to 2016. The data points selected are: number of observations, max value of market estimates of ROE according to model, min valued of dito, standard deviation in percent of dito, max value of AP, min value of AP, standard deviation in percent of AP max value of RP, min value of RP, standard deviation in percent of RP.

Appendix 3 - S&P 500 constituents used in study with 2022 financial figures[5]

https://livehhsse-my.sharepoint.com/:x:/g/personal/50743_student_hhs_se/Ef7YWVOvtU5EsKX836D7tVgBZhrJPLR2K1q6mtM-MeulrA?e=HfFsT7

Descriptive statistics of 2022 study

Descriptive statistics	
Number of observations	366
Max. of ROE	97%
Min. of ROE	3%
StdDevp of ROE	12%
Max. of RP	94%
Min. of RP	-90%
StdDevp of RP	21%

Appendix 4: Shows statistics that aim to describe the overall findings of the study conducted based on 2022 financial data. The data points selected are: number of observations, max value of market estimates of ROE according to model, min valued of dito, standard deviation in percent of dito, max value of RP, min value of RP, standard deviation in percent of RP.

[4] The data are also available from the authors on request.
[5] The data are also available from the authors on request.

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