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Do financial ratios have a statistically significant relationship with annual standard- and semi-deviation?

And do they have predicting power

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TIIVISTELMÄ:
Tässä gradussa tutkitaan, onko tilinpäätöksistä laskettavilla suhdeluvuilla statistisesti merkitsevää suhdetta saman vuoden toteutuneen volatiliteetin- ja alaspäin menevän volatiliteetin kanssa. Jos merkitsevä statistinen suhde löytyy saman vuoden toteutuneen riskin ja suhdelukujen kanssa, niin voivatko tämän vuoden suhdeluvut kertoa myös ensi vuoden riskitasosta? Sijoittajia varmasti kiinnostaa jokainen keino, joiden avulla he voivat suojata sijoitussalkkuaan liialta volatiliteetilta, etenkin alaspäin menevältä riskiltä.

Tehokkaiden markkinoiden teorian mukaan osakkeet heijastavat aina oikeaa hintaa, koska kaikki tiedettävissä oleva tieto osakkeeseen liittyen on jo hinnoiteltu osakkeeseen. Käyttäytymistieteellinen rahoituksen teoria sen sijaan viittaa siihen, että ihminen on erheellinen ja koska markkinoille osallistuu ihmisiä, rahoitusmarkkinat eivät voi olla tehokkaat. Lukuisat tutkimukset ovat osoittaneet tilinpäätösten suhdelukujen sisältävän ennustamiskykyä esimerkiksi konkurssien puolesta. Lisäksi ne ovat osoittaneet kykyä tuottaa ylituottoa. Mikäli markkinat ovat tehokkaat, tämän ei pitäisi olla mahdollista.

Tutkimuksessa on kymmenen muuttujaa (8 suhdelukua, kaikki varat, vuosi), joista tehdään regressiot vuositason normaalia- (Annual standard deviation) ja alaspäin menevää riskiä (Annual semi-deviation) vastaan. Suhdeluvut ovat return on assets, return on equity, total asset turnover, total debt % common equity, total debt % total assets, quick ratio, current ratio ja inventory turnover. Tutkielmassa on kerätty NASDAQ-osakkeista otos vuosilta 1994–2023. Hyväksytty havaintoarvo sisältää tietyn osakkeen yhden vuoden toteutuneen vuositason riskin sekä saman vuoden suhdeluvut. Jotta saadaan selville, onko toteutuneella riskillä ja saman vuoden suhdeluvuilla mitään merkitsevää suhdetta, tehdään regressiotutkimus. Tämän jälkeen tehdään uudet regressiot siten, että yhdessä havaintoarvossa on yhden vuoden riski edeltävän vuoden suhdelukuja vastaan. Näin selvitetään, paljonko suhdeluvut kertovat tulevan vuoden riskistä.

Regressiomalleja muodostuu kahdeksan. Seitsemälle kahdeksasta suhdeluvusta löytyy merkitsevä suhde vuositason keskihajonnan sekä alaspäin menevän hajonnan kanssa. Suhdeluvut yksinään selittävät saman vuoden keskihajonnasta 17,8% ja alaspäin menevästä hajonnasta 16,9%. Suhdeluvut selittävät seuraavan vuoden osalta keskihajonnasta 11,9% ja alaspäin menevästä riskistä 10,3%. Korkeimmat t-arvot muodostuvat return on assets ja return on equity -suhdeluvuille regressiomalleissa.

AVAINSANAT: Volatiliteetti, regressioanalyysi, tilinpäätösanalyysi, ennusteet, rahoitus

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1 Introduction

Rational investors seek to reduce uncertainty in their portfolios (Markowitz, 1991, p.470). This uncertainty is widely measured using variance or standard deviation for the portfolio (Connor & Korajczyk, 2010, p.8). According to the expected utility theory, investors seek to maximize the expected utility of a risky decision. An agent's attitude towards risk is defined by the shape of the utility function: An agent is defined as risk-averse when the utility function is concave, and vice versa. This has been the dominant theory concerning investor decision-making (Levy, 1992, p.173). The prospect theory by Kahneman and Tversky (1979), on the other hand, suggests that individuals evaluate an outcome depending on the degree of deviation from a certain reference point instead of with respect to net asset value. Furthermore, investors assign more weight to losses than gains, and investors are risk-averse with respect to gains and risk-seeking over losses. (Levy, 1992, p.171).

Rational investors are always seeking profitable opportunities on the stock market. If the efficient market hypothesis holds true, these profitable opportunities are not possible, as all available information is priced in the security (Fama, 1970). Thus, there are no such opportunities of extra returns for the same amount of risk. Therefore, it is hard for a single investor to beat the market with his or her own information in terms of gaining "extra" returns, as all extra returns that could be earned are already priced in the stock, removing the opportunity. This is the basic tenet of the efficient market hypothesis.

However, what if there were irrational investors? Barberis and Thaler (2003) describe multiple behavioral biases that can affect investor behavior. For example, investor over- and underreaction has been recorded by De Bondt and Thaler (1987, p.557). Behavioral biases such as overconfidence, loss aversion and gambler's fallacy (Barberis and Thaler, 2003) could cause securities' prices to deviate from their fundamental values if applied in masses and the limits of arbitrage could cause these mispricings to persist (Shleifer and Vishny, 1997). If these biases affect the stock market, then investors may not be engaging in fully rational decision-making. The justification for an asset's value would not be the same anymore for rational- and irrational investors with different amounts of information, and with limits of arbitrage (Shleifer and Vishny, 1997) the deviations from fundamental values may persist. This creates the opportunity for abnormal returns and information asymmetry.

The possibility of inefficient markets through sustained mispricing opens the possibility for the perspective that all information is not priced in the stock, meaning that some information could be hidden. The research question to present is as follows: Could financial ratios give clues of the financial well-being of a company in a simplified form? If there are irrational investors not willing to utilize the information contained in these ratios, it could give the meticulous investor looking through financial statements an advantage either in abnormal returns or less risk. This study focuses on the reduction of portfolio risk regarding standard- and downside deviation (semi-deviation)

Fundamental analysis of stocks is based on the notion that there is a link between stock price performance and the information provided by financial statement data (Abad, Thore & Laffarga, 2004). Lee (1987, p.131) states that each security has an intrinsic value that can be determined using fundamental, financial data such as earnings, growth factors and dividends. Abarbanell and Bushee (1997) show that fundamental signals have an association with earnings changes of companies. They also present evidence that analysts underreact to fundamental signal information. According to Enow (2023), key fundamental ratios provide indication of a company's financial health. For example, the price-to-earnings ratio (P/E) is a popular ratio used by analysts and investors alike (Shen, 2000, p.24) and it can give a reliable indication of the market's growth expectations (Wu, 2014, p.67). Many studies have been conducted on utilizing key fundamental ratios to increase profitability, which shall be discussed in the literature review.

Investors are always concerned with the risk of an investment, specifically the downside risk (Nawrocki, 1999, p.3). A large upswing in value does not have a negative effect on the mood of an investor looking for profits, but whenever there is a downtrend or -swing, it may cause unhappiness. This is described as loss aversion in Barberis' and Thaler's (2003) paper. If financial ratios contain information that helps investors avoid regret over lost wealth with a higher probability, the seemingly easy accessibility of these ratios and financial statement data should interest any investor.

The most common method to measure volatility is the standard deviation (Schwert, 2011, p.792). It is found to be useful because it tells how much dispersion there is in price changes for the asset, hinting on the probability of big positive- or negative swings (Schwert, 2011, p.792-793). However, Sortino and van der Meer (1991, p.27) state that a growing number of academics don't believe standard deviation and beta to be relevant for measuring risk for multiple investment situations. Sortino and van der Meer (1991, p.27) continue that uncertainty in the financial markets is described in terms of a range of possible returns and the probability of them occurring, defined as a probability distribution. The most popular distribution is the normal distribution, but the distribution of returns is anything but (Sortino and van der Meer, 1991, p.27; Estrada, 2007, p.170).

Sortino and van der Meer (1991) suggest that there is a minimum expected return for every investment decision to prevent a bad outcome. The more positive returns an investor gets, the further away he/she gets from the bad outcome, and so the less risk there is for a bad outcome. If there is a return that is between the minimum accepted return (MAR) and a 1000% gain, from the perspective of standard deviation this would be risky, since it creates dispersion around the mean return. Sortino and van der Meer (1991, p.28) state that only returns that fall below the MAR could be considered risk as it contributes to increasing unhappiness. They continue that one should distinguish between good and bad volatility (Sortino and van der Meer, 1991, p.28).

Sortino and van der Meer (1991, p.29) refer to downside variance, which remains compatible with the modern portfolio theory. In this study, risk is measured using semivariance. According to Estrada (2007, p.170) investors do not dislike upside volatility, and semivariance is useful when the distribution is either asymmetric or symmetric. Furthermore, semivariance combines variance and skewness into one. Since normality and symmetry of stock returns have been questioned by empirical evidence (Estrada, 2007, p.170) semivariance is used.

1.1 Purpose of the study

This thesis aims to research whether financial ratios have a relationship with the current and next year's annual standard- or semi-deviation. If there is a relationship, what are the most significant ratios and what are the best models for predicting risk? Using simple financial ratios in investing could potentially predict volatility, which is surely useful information for investors. Information on ratios for any given company is abundant on the internet. Finding them can be relatively easy, and if a set of ratios can be used to predict volatility, it should interest any investor. The hypotheses for this thesis are:

$H0_1$: No financial ratio has a statistically significant relationship with annual standard deviation.
$H1_1$: At least one financial ratio has a statistically significant relationship with standard deviation.
$H0_2$: No financial ratio has a statistically significant relationship with annual semi-deviation.
$H1_2$: At least one financial ratio has a statistically significant relationship with annual semi-deviation.

1.2 Structure of the study

After the introduction chapter, central theories regarding the thesis topic are explained, followed by the literature review, where multiple studies regarding financial ratios are examined. This is followed by a discussion chapter where the implications of the theories with their possibilities and contradictions are considered. The data and methodology chapter presents the data and how the study is conducted. The results are then reviewed and analyzed. The paper ends with a conclusion on the whole thesis, followed by a list of references.

2 Efficient Market Hypothesis

Fama (1965) studies the behavior of stock prices, suggesting that stock prices move according to a random walk, dividing the theory into two hypotheses: Successive price changes are independent, and price changes conform to some probability distribution. Independent price change means that the probability distribution of a price change at a certain moment is independent; It happens without regard to the past sequence of price movement. This indicates that past price history is of no real value to an investor for making predictions on price movements. Fama (1965, p.36) discusses that assets can have intrinsic values, but the market prices do not necessarily have to reflect those intrinsic values. In an uncertain world this intrinsic value is not exactly known and is disagreed upon, causing "noise" in the market. Intrinsic value can change when new information is unveiled, affecting the security's intrinsic value.

New information can be anything: Earnings news, changes in corporate governance or an escalating political situation. Fama (1965) argues that there is no reason to believe that investors have completely independent expectations from others, therefore there is a possibility of some dependency in price movements. Furthermore, information generation may not be completely independent. For example, for a company that is doing well, it can be suggested that good news is likely followed by more good news. Thus, it is suggested that there might be some level of dependence in price changes, whether it being dependence in information generation: "Good news is usually followed by good news" or investor noise generating process: "Expectations or estimates are similar across different investors".

According to Fama (1965, p.38), if a noise generating process is dependent, this indicates that investors who have a certain belief on a stock's intrinsic value can have the effect that other investors side with this investors' belief, causing many people to have the same belief. This could cause a bubble in prices, meaning a strong deviation from a stock's intrinsic value that persists. However, since there are many sophisticated investors on the market with a proper estimation of an asset's intrinsic value, they will intervene before a proper bubble can happen by either selling or buying the asset, depending on if it's overvalued or undervalued. Since sophisticated investors have a good estimate of the intrinsic value, they can sell it short when the asset is overvalued or buy it when it is undervalued. When there are enough of these sophisticated investors acting on over- or undervalued assets, prices will go back to their intrinsic values. Fama (1965, p.38) further mentions statistically able chartists pushing asset prices towards their intrinsic values as well.

According to Fama (1965, p.38) assets' intrinsic values change because of new information unveiling. If the information generation process has any dependency, sophisticated traders are assumed to learn this dependent pattern and profit from it. When there is uncertainty about the magnitude and effect of new information, investors may under- or overreact to it consistently. Sophisticated investors can take this into account and profit from the lag that exists for a moment when the price is over- or undervalued because of new information. To be exact, the mechanism that makes the price movements independent are sophisticated investors who are capable in detecting dependencies in price movements and profiting from them, and investors who can predict new information and accurately evaluating its effect on the intrinsic value of an asset (Fama, 1965, p.39). With this mechanism the price changes are made nearly independent, and the adjustment happens nearly instantaneously.

Once independence in price movement is reached, evaluating past price history becomes useless in terms of increasing expected returns. The same does not apply to the investors with the ability to accurately predict new information unveiling and its effects. When there are enough of these investors, Fama (1965, p.39) states that at this point prices are as close to their intrinsic values as can be with the available information. After running numerous tests, Fama (1965, p.90) concludes that the independence assumption of the random-walk theory is a proper description of reality. Fama further describes independence being consistent with an efficient market, where assets' prices are as close to their intrinsic values as possible and concludes that the paper presents strong evidence in favor of the random walk hypothesis.

Fama (1970) tests market efficiency in weak-form, semi-strong form, and strong form to get empirical results on how much sources of market inefficiencies affect price formation. Furthermore, dividing the tests into the three forms allows for a more detailed analysis on where the market efficiency hypothesis breaks down (Fama, 1970, p.388). All forms consider testing price adjustments with different subsets of information: Weak form considers only past prices, and capital market efficiency in its weak form is supported by mostly random walk literature (Fama, 1970, p.388). Semi-strong form takes into consideration the reaction speed of price adjustments to new information that is available to all, such as annual reports and earnings announcements. Strong form tests consider whether there are groups of investors with access to monopolistic information.

Market conditions for its efficiency are discussed in Fama (1970, p.387). For prices to fully reflect all available information, there should be no transaction costs, information related to securities is free and available to anyone, and all agree on the implications of new information on the prices of securities. Such a frictionless market does not mirror reality, however Fama (1970, p.387) states that while these conditions are sufficient for market efficiency, they are not necessary, but they can be sources of market inefficiency.

Fama (1970, p.386) describes the submartingale model that stock price sequences follow. It can be simply described as follows: The expected value of the next period's stock price, based on information Φ_t, is equal to- or greater than the current price. Fama mentions this because of its implication: A submartingale model with expected returns that are non-negative using information Φ_t indicates that a trader cannot have greater profits than a simple buy-and-hold.

Fama (1970, p.387) discusses the market conditions for efficient price adjustments to new information. A market that fully reflects all information would be free of transaction costs, all information is available to everyone and without cost, and everyone agrees on the implications of the new information. This description of a frictionless market does not mirror reality. It is then stated that the market conditions are sufficient but not necessary for market efficiency (Fama, 1970, p.387). However, while transaction costs, information that is not available to everyone and disagreement among investors do not necessarily indicate market inefficiency, they can be potential sources for it.

Weak form and semi-strong form tests support the efficient market hypothesis with a notable amount of evidence. Fama (1970, p.414) also finds that there is slight dependency in day-to-day security prices and returns that could be used for a marginally profitable trading rule, however the transaction costs incurred will consume this marginal profit.

Fama (1970, p.391) discusses the fair game model that implies that the serial covariances of stock returns are ultimately zero, meaning that the observations of a fair game variable are independent. This indicates that profitable trading rules are impossible, but it does not indicate that the serial covariances of one-period returns are zero (Fama, 1970, p.392).

Fama (1970, p.396) cites Niederhoffer and Osborne (1966) when discussing documented price behavior deviations from the random walk model. Niederhoffer and Osborne (1966) observe that reversals, consecutive price changes of opposite sign, are from two to three times more likely than continuations, consecutive price changes of the same sign. This provides evidence against the random walk model but does not count out market efficiency.

3 Limits of Arbitrage

In their paper, Shleifer and Vishny (1997, p.1) discuss the limitations of the arbitrage process of efficient markets. In the efficient market hypothesis, the sophisticated investors who spot a mispricing on the market can bring prices back to their fundamental values. Shleifer and Vishny (1997) question whether arbitrage works and if prices return to their estimated intrinsic values. Furthermore, they focus on arbitrageurs' response to irrational investor behavior (Shleifer and Vishny, 1997, p. 3). The authors state that one would assume that the further the prices deviate from their intrinsic values, the more there would be arbitrageurs looking for increased profits, taking larger positions and making the arbitrage more effective. Arbitrage is further studied from an agency perspective, that is, whether the separation of knowledge and resources lead to increased risk for the arbitrageur.

Shleifer and Vishny (1997) seek to answer how effective arbitrage is under extreme circumstances, when prices have deviated significantly from their fundamental values. The authors argue that one might think that the more prices deviate, the stronger the arbitrage activity. This argument is taken under scrutiny from an agency point of view, where the separation of knowledge and resources causes three important implications for arbitrage activity: First, since outside investors do not have the same knowledge and capability as the arbitrageur, the resources they provide for the arbitrageur are limited. Second, because of the same information asymmetry between the arbitrageur and the investor, the investors gauge the capability of the arbitrageur with past performance, dictating the willingness to provide resources. Third, since arbitrageurs are highly specialized, the arbitrage markets are segmented, and only very few professionals can attract outside investors to their arbitrage activity.

These three implications are very important for the arbitrageur. The authors state that they have a significant effect when the markets are in extreme circumstances, which is when prices deviate the most from their fundamental values. Said deviations can happen because of a change in sentiment in irrational investors, for example. Unsophisticated investors may become too enthusiastic about securities or panic about them. The paper focuses on the arbitrageurs' response to irrational price movement, seeking to show that from the agency perspective, arbitrage can be very inefficient in bringing prices back to their fundamental values.

The agency model of limits to arbitrage assumes there are three types of market participants: Noise traders, arbitrageurs and investors in arbitrage funds who do not trade themselves. Shleifer and Vishny (1997) describe a scenario where noise traders invest in an asset, causing the asset price to deviate from its fundamental value. An arbitrageur with limited resources takes a position on this because the arbitrageur knows the asset's intrinsic value. A potential scenario is presented where the mispricing deepens after noise traders invest even more on the security, causing the price to deviate further.

According to Shleifer and Vishny (1997, p.7), since arbitrageurs do not share the information and skill they have on the markets, investors who put their money on arbitrageurs do not know much themselves. If they did, they still might have a hard time understanding arbitrage, as it is a complicated concept. Therefore, investors gauge the performance of the arbitrageurs they have trusted their money to using only past performance of the arbitrageur. Furthermore, the investors form expectations based on the same information. When there are multiple arbitrageurs on the market with different levels of performance, the arbitrageurs' market shares differ as investors shift their money away from poorly performing- to the best performing arbitrageurs.

Shleifer and Vishny (1997) argue in their paper that rational investors who can mitigate arbitrage opportunities completely by spotting them and investing in them by large numbers is not possible, as real arbitrage opportunities require capital and entails a risk for them to be taken advantage of, while on the contrary the efficient market hypothesis suggests that no own capital nor risk is required from sophisticated investors to profit from arbitrage opportunities. Since arbitrage is not riskless and requires capital, asset prices might deviate from their fundamental values and remain mispriced when arbitrageurs are unable to bring the prices back due to capital- and risk constraints.

Shleifer and Vishny (1997) argue that even a simple textbook arbitrage opportunity becomes risk arbitrage, indicating that the probability of a profit is not one, that is, profit is no longer certain. Furthermore, those who can profit from arbitrage opportunities are highly specialized institutional investors who invest other peoples' money. From an agency point of view, when an investor has given their money to an individual specialized in arbitrage opportunities, the investor might not understand what the money is used for. If an arbitrageur spots a mispricing, for example a fall in stock price from its fundamental value, and takes a long position on it, the short-term irrational noise trading can cause the mispricing to become even larger, meaning that the price of the asset could fall even further from its fundamental value. At this moment the arbitrageur is making a loss on a risk arbitrage and might look incompetent in the eye of the investor.

If investors call for their money and capital becomes more restricted for the arbitrageur, he or she might be forced to liquidate a position for a loss. Therefore, capital might not be as accessible as theory suggests when there is an information asymmetry between the investor and the agent. In the case of asset prices deviating downwards from their fundamental value, if arbitrageurs are forced to liquidate their support of the asset, it leads to even further sales and the prices to deviate even more. This is an example of how even a strong mispricing could persist on the markets, consequentially allowing for market inefficiency to persist.

Since an arbitrage fund's assets are all liquid, the effect of investor withdrawals is amplified compared to an operating firm, as the fund can be completely drained of equity capital unlike firms with tangible assets (Shleifer and Vishny, 1997, p.12). This makes arbitrage funds susceptible to large, incapacitating withdrawals. In addition, investors may better understand loss of wealth during a downtrend in a firm that operates in a more conventional industry as opposed to an arbitrage fund (Shleifer and Vishny, 1997, p.12).

4 Behavioral Finance

Barberis and Thaler (2003) state that “behavioral finance argues that some financial phenomena can plausibly be understood using models in which some agents are not fully rational.” The mentioned school of thought has two “building blocks”: Limits of arbitrage and psychology. Limits of arbitrage allows mispricing to not only happen but also persist, and the psychological side of investors allows for deviations from rationality. Barberis and Thaler (2003) discuss both building blocks in their working paper and present applications of behavioral finance.

Barberis and Thaler (2003, p.3) discuss the traditional paradigm of the efficient market hypothesis, where the prices are right, and all agents are rational: Investors understand Bayes’ law and form sensible preferences. There are no free lunches on the financial markets, as no investment rule produces excess returns, that is, with the same level of risk as another investment. Arbitrage process is discussed, as in riskless profit at no cost. Barberis and Thaler (2003, p.4) state that behavioral finance rejects the possibility of this. A simple example is presented: Just because there are no free lunches on the market does not mean that the prices are right, as arbitrage is risky.

The risks that an arbitrageur faces are discussed: Fundamental risk, noise trader risk and implementation costs. The fundamental risk is the fact that a piece of bad news can bring stock prices down. This risk could be hedged through a perfect substitute of the asset, but there are hardly perfect substitutes in real markets. Noise trader risk has to do with mispricing that gets worse because of noise traders, as explained in Shleifer and Vishny (1997). This degrading situation can become even worse when arbitrageurs’ assets are taken away by investors when they call for their money back. Arbitrageurs are then unable to correct the mispricing. It should be noted that arbitrageurs can also contribute to the mispricing in case they trade in the same direction as the noise traders. The implementation cost refers to transaction costs, commissions and bid-ask spreads that make it less attractive to exploit mispricing.

Barberis and Thaler (2003, p.12) state that for any model in the financial markets it is crucial to know how investors form expectations. Psychological biases in people are discussed which can cause irrational behavior on the markets. Behavioral models usually assume a specific irrationality (Barberis and Thaler, 2003, p.11). Multiple beliefs are described, such as overconfidence, optimism, belief perseverance and more. Overconfidence indicates that people are overly confident in their judgement, and that they are not very capable of estimating probabilities. Optimism points to people displaying too optimistic views of themselves and their capabilities, such as driving skill or social skills. Belief perseverance means that once people have formed opinions, they tend to stick to them excessively, since they are unwilling to look for contradictory evidence and if they did find some, they would be very skeptical about it.

To be able to understand asset prices and investor behavior one needs to make assumptions about investor preferences (Barberis and Thaler, 2003, p.15). Most models assume that investors evaluate a gamble according to the expected utility theory, however various studies have proven investors to constantly violate this theory (Barberis and Thaler, 2003, p.15). This brings the authors to discuss the prospect theory of Kahneman and Tversky (1979), which has captured investor behavior the best (Barberis and Thaler, 2003, p.16). The prospect theory assumes that people evaluate a gamble based on the potential gains and losses, not the final wealth position. These gains and losses are relative to a reference point, which is usually the current asset position (Kahneman and Tversky, 1979, p.274).

Barberis and Thaler (2003) discuss applications of behavioral finance to different aspects of the financial markets, namely the aggregate stock market, average returns, closed-end funds and co-movement, investor behavior and corporate finance. For the aggregate stock market's behavior, the equity premium-, volatility-, and predictability puzzles are discussed. The equity premium puzzle is the investor reluctance to hold on to stocks, even though they have earned a high excess rate of return (Barberis and Thaler, 2003, p.21,24). It is suggested that investors, approximately checking on their investments annually, are loss averse over gains, therefore requiring a substantial risk premium to hold on to the stocks (Barberis and Thaler, 2003, p.26). For the volatility puzzle the behavioral approach is focused on either beliefs or preferences. It is discussed if investors believe that the mean dividend growth rate is more variable than in reality (Barberis and Thaler, 2003, p.30). Another belief-based explanation is the overconfidence of investors based on their own research on a stock, causing excessive price rises in relation to dividends if this private information is positive (Barberis and Thaler, 2003, p.30). For the preferences explanation, it is suggested that investors experience varying degrees of loss aversion depending on prior gains or losses (Barberis and Thaler, 2003, p.32).

Barberis and Thaler (2003, p.33−36) point out multiple anomalies in the financial markets that cannot be explained with traditional models. For example, size anomaly, post-earnings announcement drift, and momentum are anomalies that can hardly be explained by CAPM, for example. Barberis, Shleifer and Vishny (1998) argue that many of the anomalies are because of systematic errors investors make in evaluating their expectations of future cash flows based on public information. For example, when a company releases a positive earnings announcement, investors react insufficiently, causing the price to not rise as much as it should. The returns after this are higher on average, causing the post-earnings announcement drift and momentum in the stock price. Another explanation offered by Barberis and Thaler (2003, p.41) is institutional friction, which is anything that causes investors to be less willing to establish a short position than a long one, for example lending fees and legal restrictions. A preferences-based perspective is that investors engage in narrow framing, deriving utility from gains and losses at the level of individual stocks instead of portfolio-level (Barberis and Thaler, 2003, p.43).

Barberis and Thaler (2003, p.44) discuss closed-end funds and their deviations in price from their net asset value (NAV). When these funds are created, the price is above the NAV, however the gap closes the closer the fund gets to its termination. The reason for this, argued by behavioral finance (Barberis and Thaler, 2003, p.44−45) is irrational noise trading by fund owners, caused by irrational changes in their expectations. If fund owners must deal with the risk of changing noise trader sentiment, they require the funds to sell at a discount. The co-movement of closed funds is also discussed, specifically the fact that while closed-end fund prices move together, their fundamentals do not (Barberis and Thaler, 2003, p.46). Another explanation by Barberis and Shleifer (2003) is that investors simplify the stock picking process with categorizing stocks and then allocating their capital to said categories. If noise traders follow the same categorization, the price pressure created by this can cause correlation in stock prices with uncorrelated cash flows between each other.

Barberis and Thaler (2003, p.47) discuss investor behavior. Behavioral concepts like insufficient diversification, naïve diversification, excessive trading, the selling decision, and the buying decision are explained. Insufficient- and naïve diversification mean that investors do not diversify their portfolio as much as recommended, and even if they diversify, they do so in a naïve way. Investors also trade excessively on the market, as transaction costs consume their potential returns. The explanation offered for this is investor overconfidence, relying on their own information strongly enough to justify a trade. The selling effect is investors reluctance to sell at a loss, explained by an irrational belief of mean-reversion. The other explanation is based on prospect theory and narrow framing, specifically the concavity and convexity of the value function for gains and losses. The convexity of the value function makes the investor wait and gamble whether the stock price rises and thus saving the investor from a painful loss. The buying decisions refers to investors' tendency to buy stocks which are evenly split between prior winners and losers, while sells are mainly prior winners (Barberis and Thaler, 2003, p.52). The authors add that this may be because of investors' attention: Extreme price movements catch the eye of a potential buyer when searching for a stock.

Barberis and Thaler (2003, p.52) discuss whether the irrational investors affect investments and financing with their behavior. The authors ask how a manager who is interested in maximizing shareholder value should act when encountered with irrational investors (Barberis and Thaler, 2003, p.52). The authors refer to Stein (1996) when explaining the theoretical approach: When stock price is high, the manager should issue shares to benefit from the hype, bringing the stock price back down to the fundamental level. In contrast, when stock price is low, the manager should repurchase stocks. Evidence has shown to be consistent with theory at the aggregate level, as the share of new equity is higher during times when the stock market is highly valued (Barberis and Thaler, 2003, p.53). The evidence for this framework opens the suggestion for a theory on capital structure; If two fundamentally similar companies differ in price movement, with the other issuing more shares at a higher price peak than the other, it would explain the increase in equity for said company today (Barberis and Thaler, 2003, p.53). This theory is supported by Baker and Wurgler (2002), where a firm's weighted average book-to-market ratio, with weight placed on issues of debt or equity, is shown to be a good predictor of the fraction of equity in a firms' capital structure.

It is shown that irrational investors can affect financing decisions (Barberis and Thaler, 2003, p.54). In theory, while they may not be able to affect investment plans, they can affect the timing of security issuance. However, this only applies to firms which are not dependent on equity. Conversely, equity-dependent firms might be affected by investor sentiment: During times of negative investor sentiment, firms may have to postpone their investments because of undervalued equity due to the projects' excessive costs. (Barberis and Thaler, 2003, p.54). Investor sentiment can also affect managers when investors are overly optimistic about potential projects. If the manager refuses to take on projects that investors perceive as profitable, the investors might depress the stock price (Barberis and Thaler, 2003, p.54). Of course, the manager can also change his or her opinion because of investor sentiment: A project the manager previously perceived to be unprofitable might perceive it as profitable after investor hype (Barberis and Thaler, 2003, p.55).

The irrationality of dividends is also discussed (Barberis and Thaler, 2003, p.56-57). Investors seem to willingly accept dividends instead of share repurchases, even though dividends are taxable income while share repurchases are not. A behavioral explanation offered is that investors prefer dividends because of problems with self-control regarding consumption, leading to rules such as spending only the dividend income from the portfolio (Barberis and Thaler, 2003, p.56). Another rationale, with mental accounting as the base, is that dividends help investors separate their gains from losses, increasing utility (Barberis and Thaler, 2003, p.56). When investors are offered dividends even in the case of price decrease, it helps investors avoid regret.

5 Literature review

Kaminski, Wetzel and Guan (2004) research whether financial ratios can detect fraudulent financial reporting through investigating if financial ratios of fraudulent companies differ from those of nonfraudulent ones. It is also examined whether these differences exist prior to the fraud, after the fraud or both. 21 financial ratios are calculated from annual statements for 79 pairs of firms. The period is from three years prior- to three years post-fraud. 16 ratios are found to be significant, while only three ratios are consistently significant for three time periods. Five ratios are significant one year prior to the fraud year.

Each fraudulent firm available on SEC's Accounting and Auditing Enforcement Releases between 1982 and 1999 is used in the study. Fraudulent firms are paired with nonfraudulent firms, matching them by size, period and industry. The ratios are calculated from sample firms' income statements and balance sheets. Paired sample t-tests for each ratio are conducted to determine if there are significant differences between the mean sample values. Of the 21 ratios, 16 are found to be significant at the 10% level or less. Nine of these are significant for only one period and four ratios are significant for two periods. Only three ratios are significant for three periods.

The ratios are found to be accurate in classifying nonfraudulent firms, correctly classifying 98% of the firms. For fraudulent firms, the ratios classified correctly from 24% to 59%. The authors state that the study provides evidence on the limited ability of financial ratios in detecting fraudulent companies.

Beaver (1966) research whether financial ratios can predict firm failure, defined as the inability of a company to survive its financial obligations as they mature. 79 failed firms are classified by industry and size, and they are matched with similar non-failed firms. This paired-sample method is to control for the aforementioned factors which might affect the relationship between ratios and failure, although controlling for them also removes the predictive power of said factors.

30 ratios are calculated for each financial statement five years prior to failure unless the firm is a non-failed one. Beaver (1966) tests only existing ratios instead of developing new ones. The ratios are meant to cover as much financial information as possible with minimal overlaps, that is, ratios that use the same data. The 30 ratios are divided into six "common element" groups, and one representative ratio is picked from each group for analysis. The study states four propositions: The more liquid assets a firm has, the less chances of a failure; The larger the net-liquid asset flow from operations, the less chances of a failure; The more debt a firm has, the higher chances of a failure; The more fund expenditures for operations, the higher chances of a failure.

These four propositions can be used to create predictions for the mean values of the ratios, and evidence suggests the ratios do follow the predicted direction. As could be expected, failed firms have weaker cash flow and liquid assets compared to non-failed firms. Failed firms tend to rack up more debt as well compared to their non-failed peers. When comparing mean values of ratios between the time periods, the data demonstrates consistency and suggests that there is a difference between failed- and non-failed firms' ratios.

A classification test is conducted (Beaver, 1966), where it is predicted whether a firm is failed- or non-failed. An optimal cutoff point is found in the sorted arrays of each ratio values, minimizing the percentage of incorrect predictions. The firm is classified by whether its ratio value is above or below the cutoff. After the firms are classified, they are compared with the actual data. Beaver (1966, p.84) states that the percentage of misclassifications can be interpreted as the ratio's crude predicting capability. This test is modified so that it resembles a real-life situation more closely. Therefore, two subsamples are formed from the initial sample and the subsamples' cutoff points are found. In the first test, subsample classifications are made using the subsamples' own cutoff points, while in the second test, the classifications are made using the other subsamples' cutoff points.

The results considering the classification test -part of the study mostly discuss second-test results mentioned in the previous paragraph (Beaver, 1966, p.85). Cash-flow to total debt -ratio shows the strongest predicting capability. In the first year prior to failure, error percentage is at 13%, while in the fifth year the value is 22%. The second-strongest ratio, net income to total assets, gives 13% and 28% for first and fifth year. Total debt to total assets gives the third-best results with 19% and 28%. These percentages are much smaller than would be with a random prediction model, which would misclassify approximately 50% of the time. It is further examined what the probability of misclassifying a failed firm (Type I error) or misclassifying a non-failed firm (Type II error) is. The cash-flow to total debt ratio shows type I and II errors at 22% and 5% in the first year, respectively. For the fifth year, the corresponding values are 42% and 4%. The other ratios show higher values for the errors. Type II errors overall seem constant over the years, while type I error increases the further one gets from failure year.

The evidence suggests that ratio analysis may be useful for at least five years prior to failure. However, according to Beaver (1966, p.91), these ratios cannot be used indiscriminately. The ratios show varying predicting power, and they have differing capabilities in separating failed from non-failed firms. The author concludes that investors cannot trust ratios to eliminate the danger of picking a failing firm.

Krueger and Wrolstad (2012) construct a portfolio of 30 DJIA stocks using 15 different key fundamental metrics. While indices have traditionally been price-weighted or market capitalization-weighted, Krueger and Wrolstad (2012) build portfolios based on fundamental metrics as well. Two of the indices in the study follow the traditional indexation of price-weighting and market capitalization-weighting while the thirteen other indices are based on the DuPont equation among other measures.

After a ten-year period, the operating cash flow to current liabilities -indexed portfolio provided the highest terminal value of $1198 compared to the original $1000 invested, while the lowest terminal value was $670 on the Price/Sales indexed portfolio, providing an average loss of 2,1%. The highest annual return provided is by the Price/Dividends ratio with 36% in 2003. Standard deviations for the portfolios are found to be relatively low overall, from 17% for the capitalization-weighted portfolio to 21,4% for the Price/Dividends -weighted portfolio. The only year with a return distribution that is significantly skewed and peaked is 2008. The negative skewness is due to negative returns. All operating cash flow -based ratios provide a positive return. The ratios calculated from cash flow statements provide the most return for the long-term investor. The best and worst year was experienced by the portfolio based on the equity multiplier ratio, also having the largest standard deviation of the portfolios.

Muhammad and Scrimgeour (2014) examine appropriate financial performance measurement tools for ASX 200 companies, ASX200 being an index for Australian companies. Furthermore, it is assessed whether accounting- or market based financial measures explain stock price variance better. Five accounting-based measures are used for the study, them being return on assets, return on equity, earnings per share, free cash flow and payout ratio. The five market-based financial performance measures used are price to earnings, Tobin’s Q, market to book value, market value added and cash flow return on investment. A 9-year period from 2001 to 2010 is used for the study.

Five different models are estimated for all the performance measures, an OLS model and two sets of cross-sectional fixed- and random models. ROA is found to be statistically significant at the 1% level in four of the models, and at 5% level in the fifth model. Payout ratio is negatively statistically significant at the 1% level in three of the models, indicating that stockholders rather reinvest earnings in the company than receive dividends. For market-based measures, only market to book ratio shows consistent statistical significance in all of the models with a 1% significance level in four models and 10%

significance in one model. Muhammad and Scrimgeour (2014) conclude that the market-based measures are better for explaining stock price variance.

Abarbanell and Bushee (1997) find that there is a good economic reason for investors and analysts to rely on many fundamental signals used in Lev and Thiagarajan (1993) when evaluating firm performance in the future. Abarbanell and Bushee also find that some signals can only explain long-term earnings growth. Furthermore, Abarbanell and Bushee (1998) provide evidence that accounting-based fundamental signals can be used to predict abnormal returns. Fundamental analysis is applied in the study and 13,2% abnormal returns are recorded. Signals considering capital expenditure, changes in inventories and effective tax rate are the strongest indicators of short-term future earnings.

Altman (1968) assesses the quality of ratio analysis as an analytical technique. Altman (1968) researches this by applying five financial ratios on firms and determining whether they possess predicting capabilities considering bankruptcy. It is mentioned that ratios measuring profitability, liquidity and solvency have been the most significant indicators (Altman, 1968, p.590), however the studies Altman (1968) discusses have produced different results on which ratios are the most effective. Altman (1968) chooses to use a multiple discriminant analysis approach for determining the reliability of financial ratios.

Altman (1968) uses a sample of 66 corporations with 33 firms in each of the two groups. There is a bankrupt group and a non-bankrupt group. Five ratios are used to build the Z-score, which indicates the financial well-being of a company the higher the score is. Four of the five ratios are statistically significant at the 0,1% level. All the ratios indicate higher values the further a firm is from bankruptcy. Three variables proved to be the most capable of separating bankrupt and non-bankrupt firms, them being EBIT/Total assets, Sales/Total Assets and Market value of equity/Book value of total debt, respectively. Sales/Total assets is the only variable that is not significant at the 0,1% level but turns out to be a very important ratio on a univariate basis (Altman, 1968, p.597).

Altman (1968) estimates the values for each firm, and they are assigned to a group. They are then compared to the real results to see how accurately the model predicted bankruptcy. The model turns out to be very accurate, classifying 95% of the sample correctly using data one year prior to bankruptcy. The second test uses data two years prior to bankruptcy, and while the results are less precise, a 72% accuracy at the least is recorded, which is still relatively accurate. To control for the effect of biases, the model is applied to five subsets of the original sample and the results are evaluated using a t-test. The results indicate that the model does possess discriminating capabilities. A "zone of ignorance" is suggested for the Z-score, meaning that if a firm's score falls between 1,81 and 2,99, it is difficult to determine its financial health. For the implications it is deemed that the model is an accurate predictor of failure up to two years prior to bankruptcy. The biggest yearly value change in the ratios occur between the third and second year prior to bankruptcy.

Piotroski (2000) examines whether an accounting-based fundamental analysis strategy applied to high book-to-market firms can provide abnormal returns. The purpose of the paper is to show that investors can utilize "simple screens" that are based on historical information to create a stronger value portfolio. This happens by differentiating eventual winner stocks from losers to shift the return distribution of the portfolio, which Piotroski (2000) shows is possible.

Piotroski (2000) shows that the mean return for a high book-to-market investor can be increased by at least 7,5% by selection of financially strong high book-to-market (BM) firms. Furthermore, Piotroski (2000) shows that the return distribution is shifted to the right. Piotroski (2000) shows that the success of the investment strategy is based on predicting capabilities of future firm performance and the market's inability to do the same.

Piotroski (2000) uses nine financial signals to discriminate between firms. All firms are ranked to identify book-to-market quintile- and size tercile cutoffs. After ranking the BM quintiles, the highest BM quintile is retained for the calculation of the signals. This provides 14 043 high BM firms across 21 years. Portfolios are formed based on their F-score: Firms with the lowest F-scores are expected to have the worst returns, and vice versa. The study records whether the high F-score portfolio the other F-score portfolios, all formed from the high BM firm portfolio.

The results show that of the high-BM portfolio, 57% of the firms included produce a negative market-adjusted return. The F-score has a significant positive correlation with future returns when tested with the Spearman correlation. High F-score firms significantly outperform low F-score firms, with mean market-adjusted returns of 13,4% and -9,6%, respectively. The high F-score portfolio also outperforms the high-BM portfolio by a difference of 7,5% with a 1% statistical significance. Piotroski (2000) states that the F-score clearly discriminates between eventual winners and losers.

Piotroski (2000) also examines whether the excess returns earned by the strategy is a consequence of small-firm effect or if the strategy can be applied for all size categories. It is deemed that the largest benefit from F-score is concentrated on smaller companies, however the results are statistically significant for medium-sized firms as well, an F-score portfolio from medium-sized firms earning 7% more than the overall medium-size firm portfolio. The differences in the large firms are statistically insignificant or only marginally significant. Piotroski (2000) concludes that a simple fundamental analysis strategy can shift the return distribution earned. The mean return that is earned by a high BM investor can be increased by at least 7,5%.

6 Discussion

The literature review chapter provides some examples of the information financial ratios contain, as evidence suggests they possess predictive capabilities (Beaver, 1966; Abarbanell and Bushee, 1998; Altman, 1968) and can increase returns on the portfolio (Piotroski, 2000; Krueger and Wrolstad, 2012). For this to be possible, the markets are either slow to adjust to information in financial statements or the ratios simply contain information that the market, at least partially, overlooks. Piotroski (2000, p.1-2) suggests that markets initially underreact to historical information and that the markets do not fully account for historical financial information in prices rapidly. According to Piotroski (2000, p.38) the market slowly incorporates public historical financial information into prices and said slowness is concentrated in low-volume small firms.

Abarbanell and Bushee (1997) suggest that analyst forecasts do not completely impound the information in ratios that investors perceive them to have. They also suggest that ratios capture information that is not correlated with near-term earnings, for example shifts in firm risk. Another explanation suggested is that analysts' forecasts fail to completely impound the information in fundamental signals regarding future earnings changes, making investors utilize information in the ratios and ignoring analysts' opinions.

The possibility that ratios have persistent predicting capabilities indicates market inefficiency. Since ratios can produce abnormal returns, it means that the prices are not right on a consistent basis: If the security prices were close to their fundamental values, there would be no abnormal returns. Fama (1970, p.383) states that "A market in which prices always "fully reflect" available information is called "efficient."". If prices fully reflected all available information, they would reflect information contained in financial ratios as well. It could also be that mispricing persists, as rational investors are not taking advantage of the possibility of abnormal returns using ratios to remove the opportunity.

Since predicting capabilities exist, one would assume that the ratios can also influence portfolio risk.

7 Data & Methodology

7.1 Data

The data is obtained from the Worldscope Database. Data on the stocks of NASDAQ over the period 1993-2024 is filtered to stocks with a primary SIC code that is between 5000 – 5990. This range of SIC codes covers the wholesale- and retail industry (U.S. Securities and Exchange Commission, 2021). Wholesale and retail were chosen due to their intuitive business model and to have the maximum amount of observations: These types of companies likely provide all the necessary key figures for the study. The final sample consists of 2555 observations for the unlagged regressions, and 2184 observations for the lagged regressions. One observation is a stock's one full year's measured annual volatility, semi-deviation and all the eight non-zero financial ratios. Therefore, one observation row consists of 10 columns, of which none can be non-zero values. These columns are: Annual Std, Annual semidev, RETURN ON EQUITY - TOTAL (%), RETURN ON ASSETS, TOTAL ASSET TURNOVER, TOTAL DEBT % COMMON EQUITY, TOTAL DEBT % TOTAL ASSETS, QUICK RATIO, CURRENT RATIO, and INVENTORY TURNOVER. If any of the variables has a zero or an error value, the whole row is removed from the sample. An example would be that a stock has a full year of price activity in 2002, and annual volatility and semi-deviation are measured for that year. However, for some reason RETURN ON EQUITY - TOTAL (%) and QUICK RATIO show zero from the Worldscope Database. The row is discarded.

Annual volatility and semi-deviation are calculated on the last day of each year. The first year 1993 is dropped from the sample to ensure that there is a complete year of price activity, and 2024 is dropped completely, as it is not a full year and there are no financial ratios available for said year. Another criteria is that if a stock had a different price at the end of the next year than the previous, that indicates company activity after the observation year. However, if the price stays the same for two consequential years, both years are dropped from the sample, as the stock has likely become inactive at some point of those two years. In other words, for one observation in terms of annual volatility and semi-deviation there must be another year after the observation with a different price at the end of the year, showing that there has been price activity after the observation year has concluded.

For each stock, the years with a complete annual volatility and semi-deviation are recorded. Then, they are matched up with the same year's financial ratios for that stock from the Worldscope database. Thus, rows are formed for each ticker with the years that provide valid annual numbers and the financial ratios for the same years.

7.2 Equations

7.2.1 Annual volatility

Volatility σ of a variable is measured as the standard deviation of the return that is provided by the variable over a period when the return is measured with continuous compounding (Hull, 2023, p.164). As is presented in Hull, (2023, p.164), logarithmic returns are calculated as follows for each day of each stock in the data:

$$r_i = ln\frac{S_i}{S_{i-1}} \tag{1}$$

Where S_i is the value of a variable on day i. Assuming that the returns are independent, and variance stays the same, the variance of the continuously compounded return is T times the variance of said return on one day, meaning that the standard deviation of the return over a period of T is $\sqrt{T}$ times the standard deviation of the standard deviation of one day's return (Hull, 2023, p.164). Since annual volatility is calculated, T is the amount of trading days in a year. Since the sample trading days vary per year, the average of the whole sample's trading days is used, making T = 261. Daily volatility is calculated with the Excel function STDEV.S, which calculates sample standard deviation (Microsoft, 2024):

$$s = \sqrt{\frac{\sum(x-\bar{x})^2}{(n-1)}} \quad (2)$$

Where x is the sample mean average, and n is the sample size. In short, the calculation at the end of each observation year for each stock is as follows:

$$Annual\ Std = \sqrt{\frac{\sum(r_i-\bar{r}_{Year})^2}{(n-1)}} \times \sqrt{T} \quad (3)$$

Where r_i is the logarithmic return for day i, $\bar{r}$ is the average logarithmic return for the year in question and n is the amount of trading days during the year in question. Annual volatility is abbreviated to Annual Std when discussing the results.

7.2.2 Annual semi-deviation

Semi-deviation (abbreviated to Annual semidev in the results) is a measure of downside risk that considers volatility below a set benchmark, such as average return, risk-free rate or zero (Estrada, 2006, p.119). In his book Portfolio Selection, Harry Markowitz noted that semideviation produced preferable efficient portfolios over their standard deviation -based counterparts (Estrada, 2006). Semideviation is presented in an equation in Estrada (2006, p.119) as follows:

$$\sum_B = \sqrt{(1/T) \cdot \sum_{t=1}^{T} \{Min(R_t - B, 0\}^2} \quad (4)$$

Where T is the number of observations, B is the benchmark and R_t is return at time t. Following this example and applying the same annualizing factor $\sqrt{T}$ with T = 261, the final equation that is used to calculate annual semi-deviation for each stock for each acceptable year is as follows:

$$Annual\ semidev = \sqrt{\frac{\sum((r_i - \bar{r})^2 \times (\min(r_i - \bar{r}), 0))}{N}} \times \sqrt{T} \tag{5}$$

7.2.3 RETURN ON EQUITY - TOTAL (%)

Return on Equity (abbreviated to ROE) is an important profitability ratio for stockholders (Goel, 2015). It is calculated as the percentage of net income returned for shareholder's equity (Goel, 2015). It shows investors the productivity of a firm's equity (Fridson and Alvarez, 2011, p.284). Naturally, the higher the ratio is, the more productive the firm's equity. Ou and Penman (1989, p.307) show that a model of 16 ratios predicts earnings changes with significant ability, with closing- and opening return on equity as a part of the model. Return on Equity – Total (%), is shortened to ROE% in the equation below (Thomson Reuters, 2013):

$$ROE\% = \frac{NI - BL - PDR}{Average\ of\ Last\ Year's\ and\ Current\ Year's\ Common\ Equity * 100} \tag{6}$$

Where NI is Net Income, BL is Bottom Line and PDR is Preferred Dividend Requirement.

7.2.4 RETURN ON ASSETS

Return on Assets (abbreviated to ROA) is a ratio that measures how much profit is provided by each unit of a company's assets (Petersen and Schoeman, 2008, p.1). It is therefore a ratio of profitability. Ou and Penman (1989, p.307) find ROA to be one of the

16 statistically significant ratios as a part of a model that predicts earnings changes. Return on Assets is abbreviated to ROA in the equation below (Thomson Reuters, 2013):

$$ROA = \frac{(NI - BL + ((IED - IC) * (1 - Tax\ Rate)))}{Average\ of\ Last\ Year's\ and\ Current\ year's\ Total\ Assets * 100} \tag{7}$$

Where NI is Net Income, BL is Bottom Line, IED is Interest Expense on Debt, and IC is Interest Capitalized.

7.2.5 TOTAL ASSET TURNOVER

Altman (1968, p.595-596) describes this ratio as a standard financial ratio, describing the firm's ability to generate sales with its assets. It is categorized as an efficiency ratio (Goel, 2015). This ratio ranks as the second most contributing ratio to the discrimination of firms in Altman (1968). Total Asset Turnover also ranked as one of the most heavily weighted ratios out of fifteen for multiple discriminant models in Elam (1975, p.39). Total Asset Turnover is shortened to TAT in the equation below (Thomson Reuters, 2013):

$$TAT = \frac{Net\ Sales\ or\ Revenues}{Total\ Assets} \tag{8}$$

7.2.6 INVENTORY TURNOVER

Inventory Turnover Ratio shows how many times its inventory is sold during a financial period, showing how efficiently a company manages its inventory (Goel, 2015). Inventory Turnover Ratio is the only other available turnover ratio on Worldscope. It is found to have a positive significant effect on economic profitability for pharmaceutical companies on the Indonesian Stock Exchange (Rahayu et al., 2023). The percentage change in Inventory Turnover is a significant descriptor in Ou and Penman (1989, p.307). Inventory Turnover is shortened to ITO in the equation below (Thomson Reuters, 2013):

$$ITO = \frac{Cost\ of\ Goods\ Sold\ (excl\ Depreciation)}{Average\ of\ Last\ Year's\ and\ Current\ Year's\ Inventories} \quad (9)$$

7.2.7 TOTAL DEBT % COMMON EQUITY

Debt to Equity (D/E) is a solvency ratio (Clayman, Fridson & Troughton, 2012, p.366) and a common measure of a company's financial indebtedness (Iyer, 2018, p.158). A high D/E ratio indicates aggressive growth financing, while a low D/E may suggest a firm is too conservative, missing out on the advantages of financial leverage (Goel, 2015). According to Fridson and Alvarez (2011, p.268) lenders use the Debt-to-Equity ratio to gauge how much equity is below them by comparing it with outstanding debt. Total Debt % Common Equity is shortened to TD%CE in the equation below (Thomson Reuters, 2013):

$$TD\%CE = \frac{(LTD+STLT)}{Common\ Equity * 100} \quad (10)$$

Where LTD is Long Term Debt and STLT is Short Term Debt & Current Portion of Long-Term Debt.

7.2.8 TOTAL DEBT % TOTAL ASSETS

The Debt to Assets, categorized as a solvency ratio (Clayman, Fridson & Troughton, 2012, p.366) is a ratio that measures how much of a company's assets is financed with debt (Clayman, Fridson & Troughton, 2012, p.366). If Debt to Assets is high, it indicates that the company has a lot of debt compared to equity. This poses the problem that cash flows may be significantly reduced because of principal- and interest payments (Goel, 2015, p.143). Total Debt % Total Assets is shortened to TD%TA in the equation below (Thomson Reuters, 2013):

$$TD\%TA = \frac{(STLT + LTD)}{Total\ Assets * 100} \tag{11}$$

Where STLT is Short Term Debt & Current Portion of Long-Term Debt and LTD is Long Term Debt.

7.2.9 QUICK RATIO

The Quick Ratio is a frequently used measure of a company's liquidity, used to gauge the risk of a firm not being able to raise cash to pay its obligations (Fridson and Alvarez, 2011, p.266). It measures cash and highly liquid assets against current liabilities from the balance sheet. These highly liquid assets can be marketable securities or receivables that can be converted to cash easily (Fridson and Alvarez, 2011, p.268). The Quick Ratio equation is as follows (Thomson Reuters, 2013):

$$QUICK\ RATIO = \frac{(Cash\ \&\ Equivalents + Receivables\ (Net))}{Current\ Liabilities{-}Total} \tag{12}$$

7.2.10 CURRENT RATIO

Current Ratio measures current assets to current liabilities (Clayman, Fridson & Troughton, 2012, p.364). Generally, the higher the ratio, the better: The firm is more ready to meet short-term liabilities when the ratio is high (Goel, 2015, p.101). Too high of a Current Ratio, on the other hand, may signal idle assets (Goel, 2015, p.101). Current Ratio is found to be useful in multiple studies (Chen and Shimerda, 1981, p.52). The equation is as follows (Thomson Reuters, 2013):

$$CURRENT\ RATIO = \frac{Current\ Assets{-}Total}{Current\ Liabilities{-}Total} \quad (13)$$

7.3 Regression analysis

The relationship between key financial ratios and annual standard- and semi-deviation is researched with a multiple regression analysis. Simple regression analysis describes a relationship between an independent- and a dependent variable (Richardson, 2015, p.67). One of the assumptions of regression is that the data set consists of a random sample of variable pairs X and Y, and with sampling there are always errors (Richardson, 2015, p.41−42). This error is represented with an error term. Simple regression can be represented mathematically as follows (Richardson, 2015, p.41):

$$Y = \beta_0 + \beta_1 X + \varepsilon \quad (14)$$

Where β_0 is the intercept, β_1 is the slope and ε is the error term.

While simple regression describes a linear relationship between one independent and one dependent variable, multiple regression describes the relationship between one dependent and two or more independent variables (Richardson, 2015, p.67). The sample regression model can be expressed mathematically as (Richardson, 2015, p.71):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \varepsilon \quad (15)$$

Where β_0 is the Y-intercept and β_i is the slope of each variable's coefficient from i = 1 to k.

According to Richardson (2015, p.72−73) There are assumptions for the multiple regression:

1. For any values of the independent variable, the matching dependent variable Y values are normally distributed.

2. Equal variance assumption: The variance of normally distributed possible values for the dependent variable is the same for each value of every independent variable.

3. Linearity assumption: There is a linear relationship between the dependent variable and each independent variable. If this assumption is violated, it likely results in an insignificant independent variable in the model.

4. Nonmulticollinearity: None of the independent variables correlate with each other.

5. Independence assumption: The dependent variable observations are independent from each other, meaning that there is no correlation between successive error terms, they don't move together, and there is no trend.

Following the instructions in Richardson (2015, p.74), the data is arranged so that the dependent variables and the independent variables are next to each other, so Excel can perform the regression analysis, as it cannot execute it if the independent variables are not contiguously placed.

The purpose of the study is to research whether any of the key fundamental ratios have a statistically significant relationship with annual standard- and semi-deviation, and if previous year's ratios have a relationship with the following year's standard- and semi-deviation. This necessitates that at least one ratio's slope coefficient t-statistic is significant, and that the model's F-statistic is significant where the slope coefficient is significant. The t-statistic is used to test whether a model's estimated slope is statistically significantly different from zero (Wilson, Holton & Hodges, 2012, p.43). The hypothesis testing can be expressed in mathematical terms as follows, similarly applying to $H0_2$ and $H1_2$:

$$H0_1: \beta_1 = \beta_2 = \beta_3 \dots = \beta_8 = 0 \tag{16}$$

$$H1_1: \beta_k \neq 0 \tag{17}$$

A two-tailed t-test is conducted with a 95% confidence level, indicating a level of significance of α = 0,05. The null hypothesis is rejected if the absolute value of the calculated t-statistic is equal to or greater than the critical value of the set confidence level (Wilson, Holton & Hodges, 2012, p.47)

According to Wilson, Holton & Hodges (2012, p.85), The F-test is used to test for the significance of the overall regression model. The same null hypothesis applies here, that all the slope coefficients equal zero. The alternative hypothesis is that at least one coefficient is not zero.

According to Richardson (2015, p.154), a rule of thumb is that a correlation of 0,6 or above between independent variables is something to be concerned about when it comes to multicollinearity. As shown below in Table 1, the correlations that cross the 0,6 threshold are Return on Equity-Return on Assets with 0,85, Quick Ratio-Current ratio with 0,78, Total Debt % Total Assets-Total Debt % Common Equity. In the final model one of the variables with strong correlation to another is always dropped.

Extreme outliers are accounted for by removing observations that contain values which are higher than the 99,5th percentile or smaller than the 0,5th percentile for any independent variable. 159 observations are removed, leaving a total of 2555 observations for the regression runs without lagged variables. The same dataset is used for the lagged ratios, but more observations are omitted, as will be explained further below.

According to Richardson (2015, p.94), autocorrelation is when the error terms or residuals correlate with each other. This is a violation of one of the assumptions of regression, and therefore needs to be accounted for. To test whether the residuals contain autocorrelation, a Durbin-Watson test is performed. The Durbin-Watson test only spots first-order autocorrelation (Richardson, 2015, p.160).

The Durbin-Watson test can produce a value between zero and four. A value of two indicates no autocorrelation, whereas a value close to zero indicates positive autocorrelation and a value closer to four indicates negative autocorrelation. The Durbin-Watson test is defined as follows (Richardson, 2015, p.160):

$$d = \frac{\sum_{i=2}^{n}(e_i - e_{i-1})^2}{\sum_{i=1}^{n} e_i^2} \tag{18}$$

A two-tailed test will be utilized, since there is no clear assumption about whether the independent variables' coefficient slopes will be positive or negative. If autocorrelation is present, then the Year-variable should be statistically significant and capture it (Richardson, 2015, p.164).

Following Richardson (2015, p.115-116) a series of multiple regressions is conducted, dropping the most insignificant variable one at a time until arriving at a model where all the coefficient slopes and the model itself are significant. For the unlagged ratios this is simply running a series of regressions, first with Annual Std as the dependent variable and then Annual semidev. In practice, this is done by running a regression with Excel, moving one variable's column out of the next regression, running the regression again and the process is repeated until all variables have been left out of the regression once. Then, the variable that's absence caused the smallest drop in R^2 is removed completely from the next series of regressions. This process is repeated until we arrive at a final model that is significant in terms of F-significance and all the variables' slopes have a significant t-statistic at the 5% level.

For testing whether previous year's ratios have predicting capabilities, all variables need to be lagged so that one stock's next value is attempted to be forecasted with the same stock's previous year's value. Since the dataset has observations from different years and 274 different stocks, simply lagging the variables one step below the dependent variables is not the proper approach, as there would be overlap between the values of different stocks, as shown below:

Ticker	Year	Annual Std	Annual semidev	TOTAL ASS	RETURN O	RETURN O	TOTAL ASS	TOTAL DEE	TOTAL DEE	QUICK RAT	CURRENT	INVENTOR
545983	1995	0,311481624	0,206559487	89712	18,3	11,67	1,05	71,95	38,48	0,45	3,11	1,41
545983	1996	0,279010993	0,199718489	91497	14,6	10,06	1,19	40,65	26,59	0,78	4,6	1,25
545983	1997	0,553354708	0,411417469	142082	3,83	3,6	0,86	118,33	49,42	0,49	3	1,29
874859	1998	0,558527828	0,402974208	119696	20,47	14,67	2,2	16,39	13,31	1,59	4,36	3,09
874859	1999	0,534864095	0,385708251	192048	13,64	11,42	1,73	2	1,7	1,81	4,97	2,83
874859	2000	0,562919003	0,393937807	180703	6,26	5,6	2,06	8,45	7,02	0,96	3,7	2,68
874859	2001	0,566373795	0,40983114	181032	-0,32	0,26	1,94	10,26	8,27	0,93	3,51	2,42
874859	2002	0,460069594	0,328823735	150721	-16,19	-13,01	2,54	5,48	4,59	1,18	4,04	2,6
874859	2003	0,322124595	0,220090531	184532	11,01	9,01	2,38	11,73	9,01	0,91	3,23	2,65
874859	2004	0,375969323	0,266844647	210144	11,32	9,2	2,38	5,83	4,76	1,1	3,85	2,64
874859	2006	0,447893384	0,368336782	286119	10,73	8,8	2,2	4,28	3,34	0,96	3,22	2,72
@RAUT	1994	0,408544099	0,291153097	78258	11,64	7,03	1,77	48,73	24,98	0,94	3,8	2,26
@RAUT	1995	0,345169376	0,247009917	99788	4,53	3,45	1,55	74,56	32,13	0,79	3,22	1,98
@RAUT	1996	0,379524597	0,272153831	105717	11,19	6,36	1,75	76,69	34,89	0,9	4,11	1,96
@RAUT	1997	0,351575553	0,247147561	93576	6,54	4,8	2,02	49,04	27,02	1,17	4,86	2,05
@BMCH	2014	0,393754771	0,272810295	371218	7,76	3,53	3,49	69,41	26,34	1,21	2,29	9,57
@BMCH	2015	0,394681646	0,267715527	1376008	-1,2	1,38	1,15	68,64	31,37	1,18	2,21	6,39
@BMCH	2016	0,346877497	0,268470211	1394464	4,72	3,64	2,22	55,33	27	1,14	2,2	8,29
@BMCH	2017	0,263427831	0,192843961	1473350	8,05	5,14	2,28	49,76	25,22	1,15	2,33	8,05
@BMCH	2018	0,316249554	0,20615897	1576111	14,77	9,1	2,34	41,24	22,89	1,69	2,86	8,54
@BMCH	2019	0,278614943	0,173487307	1906101	11,84	7,36	1,9	38,5	19,82	1,41	2,38	8,3
277874	2000	0,483184246	0,332433369	242900	18,34	7,85	4,42	100,12	33,39	1,02	1,88	11,41
277874	2001	0,346272042	0,226704196	239100	7,12	5,06	3,95	93,05	30,78	0,91	1,82	10,55
277874	2002	0,403400066	0,285395571	221900	-15,89	-2,43	3,93	99,56	30,6	0,74	1,72	9,08
277874	2003	0,691056967	0,480730872	218400	4,84	3,46	4,16	93,91	31,04	0,88	1,89	8,93

Figure 1. Dataset demonstration without lagged variables.

Lagging the variables one step below the dependent variables (Annual Std, Annual semidev) would cause the overlap of the first- and last years of different stocks (Year added to the right side for demonstration):

Ticker	Year	Annual Std	Annual semidev	TOTAL ASS	RETURN O	RETURN O	TOTAL ASS	TOTAL DEE	TOTAL DEE	QUICK RA	CURRENT	INVENTOR	Year
545983	1995	0,311481624	0,206559487										
545983	1996	0,279010993	0,199718489	89712	18,3	11,67	1,05	71,95	38,48	0,45	3,11	1,41	1995
545983	1997	0,553354708	0,411417469	91497	14,6	10,06	1,19	40,65	26,59	0,78	4,6	1,25	1996
874859	1998	0,558527828	0,402974208	142082	3,83	3,6	0,86	118,33	49,42	0,49	3	1,29	1997
874859	1999	0,534864095	0,385708251	119696	20,47	14,67	2,2	16,39	13,31	1,59	4,36	3,09	1998
874859	2000	0,562919003	0,393937807	192048	13,64	11,42	1,73	2	1,7	1,81	4,97	2,83	1999
874859	2001	0,566373795	0,40983114	180703	6,26	5,6	2,06	8,45	7,02	0,96	3,7	2,68	2000
874859	2002	0,460069594	0,328823735	181032	-0,32	0,26	1,94	10,26	8,27	0,93	3,51	2,42	2001
874859	2003	0,322124595	0,220090531	150721	-16,19	-13,01	2,54	5,48	4,59	1,18	4,04	2,6	2002
874859	2004	0,375969323	0,266844647	184532	11,01	9,01	2,38	11,73	9,01	0,91	3,23	2,65	2003
874859	2006	0,447893384	0,368336782	210144	11,32	9,2	2,38	5,83	4,76	1,1	3,85	2,64	2004
@RAUT	1994	0,408544099	0,291153097	286119	10,73	8,8	2,2	4,28	3,34	0,96	3,22	2,72	2006
@RAUT	1995	0,345169376	0,247009917	78258	11,64	7,03	1,77	48,73	24,98	0,94	3,8	2,26	1994
@RAUT	1996	0,379524597	0,272153831	99788	4,53	3,45	1,55	74,56	32,13	0,79	3,22	1,98	1995
@RAUT	1997	0,351575553	0,247147561	105717	11,19	6,36	1,75	76,69	34,89	0,9	4,11	1,96	1996
@BMCH	2014	0,393754771	0,272810295	93576	6,54	4,8	2,02	49,04	27,02	1,17	4,86	2,05	1997
@BMCH	2015	0,394681646	0,267715527	371218	7,76	3,53	3,49	69,41	26,34	1,21	2,29	9,57	2014
@BMCH	2016	0,346877497	0,268470211	1376008	-1,2	1,38	1,15	68,64	31,37	1,18	2,21	6,39	2015
@BMCH	2017	0,263427831	0,192843961	1394464	4,72	3,64	2,22	55,33	27	1,14	2,2	8,29	2016
@BMCH	2018	0,316249554	0,20615897	1473350	8,05	5,14	2,28	49,76	25,22	1,15	2,33	8,05	2017
@BMCH	2019	0,278614943	0,173487307	1576111	14,77	9,1	2,34	41,24	22,89	1,69	2,86	8,54	2018
277874	2000	0,483184246	0,332433369	1906101	11,84	7,36	1,9	38,5	19,82	1,41	2,38	8,3	2019
277874	2001	0,346272042	0,226704196	242900	18,34	7,85	4,42	100,12	33,39	1,02	1,88	11,41	2000
277874	2002	0,403400066	0,285395571	239100	7,12	5,06	3,95	93,05	30,78	0,91	1,82	10,55	2001
277874	2003	0,691056967	0,480730872	221900	-15,89	-2,43	3,93	99,56	30,6	0,74	1,72	9,08	2002
277874	2004	0,572795514	0,322836343	218400	4,84	3,46	4,16	93,91	31,04	0,88	1,89	8,93	2003

Figure 2. Overlapping observations.

The simple lagging of all the variables one step below the dependent variables causes the 2006 independent variables of ticker 874859 to be matched with the Annual Std and Annual Semidev of @RAUT in 1994, and 1997 variables of @RAUT to be matched with the Annual Std and Annual semidev of @BMCH in 2014. Obviously, this can significantly affect the results regarding the ability of previous years' variables to forecast the next year's Annual Std and Annual semidev. To solve this, the first-year observations of each ticker are deleted where the overlaps happen. In the picture below, all overlaps in the example are highlighted first, and then deleted:

Ticker	Year	Annual Std	Annual semidev	TOTAL ASS	RETURN O	RETURN O	TOTAL ASS	TOTAL DEE	TOTAL DEE	QUICK RA	CURRENT	INVENTOR	Year
545983	1995	0,311481624	0,206559487										
545983	1996	0,279010993	0,199718489	89712	18,3	11,67	1,05	71,95	38,48	0,45	3,11	1,41	1995
545983	1997	0,553354708	0,411417469	91497	14,6	10,06	1,19	40,65	26,59	0,78	4,6	1,25	1996
874859	1998	0,558527828	0,402974208	142082	3,83	3,6	0,86	118,33	49,42	0,49	3	1,29	1997
874859	1999	0,534864095	0,385708251	119696	20,47	14,67	2,2	16,39	13,31	1,59	4,36	3,09	1998
874859	2000	0,562919003	0,393937807	192048	13,64	11,42	1,73	2	1,7	1,81	4,97	2,83	1999
874859	2001	0,566373795	0,40983114	180703	6,26	5,6	2,06	8,45	7,02	0,96	3,7	2,68	2000
874859	2002	0,460069594	0,328823735	181032	-0,32	0,26	1,94	10,26	8,27	0,93	3,51	2,42	2001
874859	2003	0,322124595	0,220090531	150721	-16,19	-13,01	2,54	5,48	4,59	1,18	4,04	2,6	2002
874859	2004	0,375969323	0,266844647	184532	11,01	9,01	2,38	11,73	9,01	0,91	3,23	2,65	2003
874859	2006	0,447893384	0,368336782	210144	11,32	9,2	2,38	5,83	4,76	1,1	3,85	2,64	2004
@RAUT	1994	0,408544099	0,291153097	286119	10,73	8,8	2,2	4,28	3,34	0,96	3,22	2,72	2006
@RAUT	1995	0,345169376	0,247009917	78258	11,64	7,03	1,77	48,73	24,98	0,94	3,8	2,26	1994
@RAUT	1996	0,379524597	0,272153831	99788	4,53	3,45	1,55	74,56	32,13	0,79	3,22	1,98	1995
@RAUT	1997	0,351575553	0,247147561	105717	11,19	6,36	1,75	76,69	34,89	0,9	4,11	1,96	1996
@BMCH	2014	0,393754771	0,272810295	93576	6,54	4,8	2,02	49,04	27,02	1,17	4,86	2,05	1997
@BMCH	2015	0,394681646	0,267715527	371218	7,76	3,53	3,49	69,41	26,34	1,21	2,29	9,57	2014
@BMCH	2016	0,346877497	0,268470211	1376008	-1,2	1,38	1,15	68,64	31,37	1,18	2,21	6,39	2015
@BMCH	2017	0,263427831	0,192843961	1394464	4,72	3,64	2,22	55,33	27	1,14	2,2	8,29	2016
@BMCH	2018	0,316249554	0,20615897	1473350	8,05	5,14	2,28	49,76	25,22	1,15	2,33	8,05	2017
@BMCH	2019	0,278614943	0,173487307	1576111	14,77	9,1	2,34	41,24	22,89	1,69	2,86	8,54	2018
277874	2000	0,483184246	0,332433369	1906101	11,84	7,36	1,9	38,5	19,82	1,41	2,38	8,3	2019
277874	2001	0,346272042	0,226704196	242900	18,34	7,85	4,42	100,12	33,39	1,02	1,88	11,41	2000
277874	2002	0,403400066	0,285395571	239100	7,12	5,06	3,95	93,05	30,78	0,91	1,82	10,55	2001
277874	2003	0,691056967	0,480730872	221900	-15,89	-2,43	3,93	99,56	30,6	0,74	1,72	9,08	2002
277874	2004	0,572795514	0,322836343	218400	4,84	3,46	4,16	93,91	31,04	0,88	1,89	8,93	2003

Figure 3. Overlapping observations highlighted before deleting them.

Ticker	Year	Annual Std	Annual semidev	TOTAL ASS	RETURN O	RETURN O	TOTAL ASS	TOTAL DEE	TOTAL DEE	QUICK RA	CURRENT	INVENTOR	Year
545983	1995	0,311481624	0,206559487										
545983	1996	0,279010993	0,199718489	89712	18,3	11,67	1,05	71,95	38,48	0,45	3,11	1,41	1995
545983	1997	0,553354708	0,411417469	91497	14,6	10,06	1,19	40,65	26,59	0,78	4,6	1,25	1996
874859	1999	0,534864095	0,385708251	119696	20,47	14,67	2,2	16,39	13,31	1,59	4,36	3,09	1998
874859	2000	0,562919003	0,393937807	192048	13,64	11,42	1,73	2	1,7	1,81	4,97	2,83	1999
874859	2001	0,566373795	0,40983114	180703	6,26	5,6	2,06	8,45	7,02	0,96	3,7	2,68	2000
874859	2002	0,460069594	0,328823735	181032	-0,32	0,26	1,94	10,26	8,27	0,93	3,51	2,42	2001
874859	2003	0,322124595	0,220090531	150721	-16,19	-13,01	2,54	5,48	4,59	1,18	4,04	2,6	2002
874859	2004	0,375969323	0,266844647	184532	11,01	9,01	2,38	11,73	9,01	0,91	3,23	2,65	2003
874859	2006	0,447893384	0,368336782	210144	11,32	9,2	2,38	5,83	4,76	1,1	3,85	2,64	2004
@RAUT	1995	0,345169376	0,247009917	78258	11,64	7,03	1,77	48,73	24,98	0,94	3,8	2,26	1994
@RAUT	1996	0,379524597	0,272153831	99788	4,53	3,45	1,55	74,56	32,13	0,79	3,22	1,98	1995
@RAUT	1997	0,351575553	0,247147561	105717	11,19	6,36	1,75	76,69	34,89	0,9	4,11	1,96	1996
@BMCH	2015	0,394681646	0,267715527	371218	7,76	3,53	3,49	69,41	26,34	1,21	2,29	9,57	2014
@BMCH	2016	0,346877497	0,268470211	1376008	-1,2	1,38	1,15	68,64	31,37	1,18	2,21	6,39	2015
@BMCH	2017	0,263427831	0,192843961	1394464	4,72	3,64	2,22	55,33	27	1,14	2,2	8,29	2016
@BMCH	2018	0,316249554	0,20615897	1473350	8,05	5,14	2,28	49,76	25,22	1,15	2,33	8,05	2017
@BMCH	2019	0,278614943	0,173487307	1576111	14,77	9,1	2,34	41,24	22,89	1,69	2,86	8,54	2018
277874	2001	0,346272042	0,226704196	242900	18,34	7,85	4,42	100,12	33,39	1,02	1,88	11,41	2000
277874	2002	0,403400066	0,285395571	239100	7,12	5,06	3,95	93,05	30,78	0,91	1,82	10,55	2001
277874	2003	0,691056967	0,480730872	221900	-15,89	-2,43	3,93	99,56	30,6	0,74	1,72	9,08	2002
277874	2004	0,572795514	0,322836343	218400	4,84	3,46	4,16	93,91	31,04	0,88	1,89	8,93	2003

Figure 4. Overlapping observations deleted.

Now the 1994 ratios of @RAUT are matched with 1995 Annual Std and Annual semidev of @RAUT, 2015 ratios of @BMCH are matched with 2016 Annual Std and Annual semidev of @BMCH, and so on. This leads to 274 observations being deleted. The dataset thus contains 2281 observations for this part of the regression analysis.

7.4 Descriptive statistics

Table 1. Descriptive statistics for the dependent variables (normal regression)

Annual Std		*Annual semidev*	
Mean	0,5275878	Mean	0,3681808
Standard Error	0,0053298	Standard Error	0,0037143
Median	0,4616203	Median	0,3235522
Mode	#N/A	Mode	#N/A
Standard Deviation	0,2694045	Standard Deviation	0,1877488
Sample Variance	0,0725788	Sample Variance	0,0352496
Kurtosis	5,2527844	Kurtosis	6,3355068
Skewness	1,7901184	Skewness	1,8366053
Range	2,5863473	Range	2,1468942
Minimum	0,0254818	Minimum	0,0184482
Maximum	2,611829	Maximum	2,1653425
Sum	1347,9868	Sum	940,70195
Count	2555	Count	2555

Table 2. Descriptive statistics for Total Assets, Return on Equity and Return on Assets (normal regression)

TOTAL ASSETS (U.S.$)		*RETURN ON EQUITY - TOTAL (%)*		*RETURN ON ASSETS*	
Mean	2886394	Mean	6,999002	Mean	4,195679
Standard Error	385046,5	Standard Error	0,563558	Standard Error	0,206836
Median	376193	Median	10,54	Median	5,63
Mode	341487	Mode	4,72	Mode	5,75
Standard Deviation	19462950	Standard Deviation	28,48615	Standard Deviation	10,45494
Sample Variance	3,79E+14	Sample Variance	811,4607	Sample Variance	109,3058
Kurtosis	420,9156	Kurtosis	18,76435	Kurtosis	13,40051
Skewness	18,92161	Skewness	-2,31845	Skewness	-2,68032
Range	5,15E+08	Range	475,65	Range	116,04
Minimum	4505	Minimum	-265,22	Minimum	-82,33
Maximum	5,15E+08	Maximum	210,43	Maximum	33,71
Sum	7,37E+09	Sum	17882,45	Sum	10719,96
Count	2555	Count	2555	Count	2555

Table 3. Descriptive statistics for Total Asset Turnover, Total Debt % Common Equity and Total Debt % Total Assets.

TOTAL ASSET TURNOVER		*TOTAL DEBT % COMMON EQUITY*		*TOTAL DEBT % TOTAL ASSETS*	
Mean	2,17922	Mean	73,57786	Mean	20,86255
Standard Error	0,02167	Standard Error	2,226662	Standard Error	0,317749
Median	2	Median	39,25	Median	18,03
Mode	1,33	Mode	0,06	Mode	0,07
Standard Deviation	1,09548	Standard Deviation	112,5511	Standard Deviation	16,06124
Sample Variance	1,20008	Sample Variance	12667,76	Sample Variance	257,9635
Kurtosis	3,04538	Kurtosis	32,56308	Kurtosis	-0,179476
Skewness	1,25245	Skewness	4,544946	Skewness	0,717641
Range	9,09	Range	1414,41	Range	72,19
Minimum	0,24	Minimum	0,03	Minimum	0,03
Maximum	9,33	Maximum	1414,44	Maximum	72,22
Sum	5567,91	Sum	187991,4	Sum	53303,82
Count	2555	Count	2555	Count	2555

Table 4. Descriptive statistics for Quick Ratio, Current Ratio, Inventory Turnover and Year (normal regression).

QUICK RATIO		*CURRENT RATIO*		*INVENTORY TURNOVER*		*YEAR*	
Mean	0,897941	Mean	1,741973	Mean	21,332384	Mean	2007,32
Standard Error	0,01492	Standard Error	0,02191	Standard Error	0,5664341	Standard Error	0,16799
Median	0,73	Median	1,49	Median	9,69	Median	2006
Mode	0,15	Mode	1,31	Mode	6,05	Mode	1999
Standard Deviation	0,754172	Standard Deviation	1,107477	Standard Deviation	28,631548	Standard Deviation	8,49136
Sample Variance	0,568776	Sample Variance	1,226506	Sample Variance	819,76554	Sample Variance	72,1031
Kurtosis	6,578161	Kurtosis	4,158597	Kurtosis	11,002708	Kurtosis	-1,14276
Skewness	2,058858	Skewness	1,69673	Skewness	2,9639003	Skewness	0,22772
Range	5,77	Range	7,9	Range	203,14	Range	29
Minimum	0,05	Minimum	0,26	Minimum	0,54	Minimum	1994
Maximum	5,82	Maximum	8,16	Maximum	203,68	Maximum	2023
Sum	2294,24	Sum	4450,74	Sum	54504,24	Sum	5128690
Count	2555	Count	2555	Count	2555	Count	2555

Table 5. Descriptive statistics for Annual Std and Annual semidev (lagged regression)

Annual Std		*Annual semidev*	
Mean	0,514482646	Mean	0,359442725
Standard Error	0,005444313	Standard Error	0,003824549
Median	0,452418762	Median	0,31664017
Mode	#N/A	Mode	#N/A
Standard Deviation	0,260019379	Standard Deviation	0,182659744
Sample Variance	0,067610077	Sample Variance	0,033364582
Kurtosis	4,81321765	Kurtosis	7,096240029
Skewness	1,758826642	Skewness	1,909279204
Range	2,273503109	Range	2,069597915
Minimum	0,133763182	Minimum	0,095744583
Maximum	2,407266291	Maximum	2,165342497
Sum	1173,534915	Sum	819,8888547
Count	2281	Count	2281

Table 6. Descriptive statistics for lagged Total Assets, Return on Equity and Return on Assets.

TOTAL ASSETS (U.S.$) LAG 1		*RETURN ON EQUITY - TOTAL (%) LAG 1*		*RETURN ON ASSETS LAG 1*	
Mean	2769706,174	Mean	7,49868917	Mean	4,506348093
Standard Error	363423,2019	Standard Error	0,55479344	Standard Error	0,205995139
Median	379748	Median	10,85	Median	5,7
Mode	341487	Mode	4,72	Mode	8,26
Standard Deviation	17357025,16	Standard Deviation	26,4968324	Standard Deviation	9,838289884
Sample Variance	3,01266E+14	Sample Variance	702,082129	Sample Variance	96,79194784
Kurtosis	415,6106491	Kurtosis	22,5846903	Kurtosis	14,83537285
Skewness	18,54918108	Skewness	-2,7597966	Skewness	-2,6814713
Range	455157495	Range	460,64	Range	116,04
Minimum	4505	Minimum	-265,22	Minimum	-82,33
Maximum	455162000	Maximum	195,42	Maximum	33,71
Sum	6317699784	Sum	17104,51	Sum	10278,98
Count	2281	Count	2281	Count	2281

Table 7. Descriptive statistics for lagged Total Asset Turnover, Total Debt % Common Equity and Total Debt % Total Assets.

TOTAL ASSET TURNOVER LAG 1		*TOTAL DEBT % COMMON EQUITY LAG 1*		*TOTAL DEBT % TOTAL ASSETS LAG 1*	
Mean	2,200175362	Mean	71,63149496	Mean	20,9957431
Standard Error	0,022667699	Standard Error	2,222514061	Standard Error	0,335354197
Median	2,01	Median	39,39	Median	18,32
Mode	1,33	Mode	0,06	Mode	0,07
Standard Deviation	1,082605112	Standard Deviation	106,1468621	Standard Deviation	16,01645465
Sample Variance	1,172033829	Sample Variance	11267,15633	Sample Variance	256,5268195
Kurtosis	2,737234409	Kurtosis	35,44228896	Kurtosis	-0,21200236
Skewness	1,195269434	Skewness	4,584531262	Skewness	0,700511565
Range	9,09	Range	1414,41	Range	72,19
Minimum	0,24	Minimum	0,03	Minimum	0,03
Maximum	9,33	Maximum	1414,44	Maximum	72,22
Sum	5018,6	Sum	163391,44	Sum	47891,29
Count	2281	Count	2281	Count	2281

Table 8. Descriptive statistics for lagged Quick Ratio and Current Ratio.

QUICK RATIO LAG 1		*CURRENT RATIO LAG 1*	
Mean	0,889552828	Mean	1,74003069
Standard Error	0,015376992	Standard Error	0,02284514
Median	0,73	Median	1,5
Mode	0,25	Mode	1,33
Standard Deviation	0,734402294	Standard Deviation	1,09107956
Sample Variance	0,53934673	Sample Variance	1,1904546
Kurtosis	6,359074193	Kurtosis	4,02354029
Skewness	1,998948233	Skewness	1,67439606
Range	5,73	Range	7,9
Minimum	0,05	Minimum	0,26
Maximum	5,78	Maximum	8,16
Sum	2029,07	Sum	3969,01
Count	2281	Count	2281

Table 9. Descriptive statistics for lagged Inventory Turnover and Year.

INVENTORY TURNOVER LAG 1		*YEAR LAG 1*	
Mean	21,03097764	Mean	2006,8356
Standard Error	0,592025502	Standard Error	0,17106648
Median	9,76	Median	2006
Mode	6,05	Mode	1999
Standard Deviation	28,2750289	Standard Deviation	8,17010354
Sample Variance	799,4772594	Sample Variance	66,7505918
Kurtosis	11,99863366	Kurtosis	-1,1343851
Skewness	3,076378575	Skewness	0,22462863
Range	203	Range	28
Minimum	0,68	Minimum	1994
Maximum	203,68	Maximum	2022
Sum	47971,66	Sum	4577592
Count	2281	Count	2281

7.5 Correlation matrices

Table 10. Correlation matrix for the unlagged independent variables.

	TOTAL ASSETS (U.S.$)	RETURN ON EQUITY - TOTAL (%)	RETURN ON ASSETS	TOTAL ASSET TURNOVER	TOTAL DEBT % COMMON	TOTAL DEBT % TOTAL ASSETS	QUICK RATIO	CURRENT RATIO	INVENTORY TURNOVER	YEAR
YEAR										1,000
INVENTORY TURNOVER									1,000	0,054
CURRENT RATIO								1,000	-0,336	-0,093
QUICK RATIO							1,000	0,785	-0,058	-0,009
TOTAL DEBT % TOTAL ASSETS						1,000	-0,132	-0,113	0,075	-0,026
TOTAL DEBT % COMMON					1,000	0,729	-0,100	-0,143	0,099	0,075
TOTAL ASSET TURNOVER				1,000	-0,012	-0,044	-0,144	-0,064	-0,118	-0,174
RETURN ON ASSETS			1,000	0,072	-0,076	-0,059	-0,001	0,064	0,001	-0,031
RETURN ON EQUITY - TOTAL (%)		1,000	0,853	0,079	0,013	-0,027	-0,010	0,021	0,023	0,033
TOTAL ASSETS (U.S.$)	1,000	0,053	0,032	-0,040	0,003	-0,005	-0,031	-0,063	-0,033	0,153

Table 11. Correlation matrix for the lagged variables.

YEAR LAG 1										1,000
INVENTORY TURNOVER LAG 1									1,000	0,048
CURRENT RATIO LAG 1								1,000	-0,340	-0,083
QUICK RATIO LAG 1							1,000	0,781	-0,062	0,001
TOTAL DEBT % TOTAL ASSETS LAG 1						1,000	-0,129	-0,113	0,077	-0,031
TOTAL DEBT % COMMON EQUITY LAG 1					1,000	0,749	-0,110	-0,147	0,085	0,048
TOTAL ASSET TURNOVER LAG 1				1,000	0,003	-0,041	-0,142	-0,065	-0,119	-0,158
RETURN ON ASSETS LAG 1			1,000	0,070	-0,081	-0,059	-0,034	0,039	0,000	-0,005
RETURN ON EQUITY - TOTAL (%) LAG 1		1,000	0,850	0,078	-0,020	-0,032	-0,033	0,004	0,015	0,052
TOTAL ASSETS (U.S.$) LAG 1	1,000	0,056	0,031	-0,039	0,004	-0,003	-0,033	-0,066	-0,032	0,162
	TOTAL ASSETS (U.S.$) LAG 1	RETURN ON EQUITY - TOTAL (%) LAG 1	RETURN ON ASSETS LAG 1	TOTAL ASSET TURNOVER LAG 1	TOTAL DEBT % COMMON EQUITY LAG 1	TOTAL DEBT % TOTAL ASSETS LAG 1	QUICK RATIO LAG 1	CURRENT RATIO LAG 1	INVENTORY TURNOVER LAG 1	YEAR LAG 1

8 Results

In this chapter the results of the regression analysis are discussed, with the unlagged regressions being Annual Std – All independent variables, Annual Std – Only ratios, Annual semidev – All independent variables, Annual semidev – Only ratios. The same is repeated with lagged independent variables, which makes Annual Std – All lagged variables, Annual Std – Lagged ratios, Annual semidev – All lagged variables and Annual semidev – Only ratios. This provides us with a total of eight significant regression models. All the regression models are significant at the 5% level regarding the t-statistic and F-significance.

8.1 Annual Std – All Independent Variables

Table 12. Final regression model for Annual Std - All Independent Variables.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,483918
R Square	0,234177
Adjusted R Square	0,232373
Standard Error	0,236037
Observations	2555

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	6	43,40841	7,234734	129,85625	1,1E-143
Residual	2548	141,9578	0,055713		
Total	2554	185,3662			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	13,98106	1,138934	12,27556	1,076E-33	11,74773	16,21439	11,74773	16,21439

TOTAL ASSETS (U.S.$)	-7,8E-10	2,43E-10	-3,20192	0,001382	-1,3E-09	-3E-10	-1,3E-09	-3E-10
RETURN ON ASSETS	-0,01063	0,00045	-23,6411	6,97E-112	-0,01151	-0,00975	-0,01151	-0,00975
TOTAL ASSET TURNOVER	0,019567	0,004389	4,457896	8,635E-06	0,01096	0,028174	0,01096	0,028174
TOTAL DEBT % COMMON EQUITY	0,000112	4,19E-05	2,672668	0,007573	2,99E-05	0,000194	2,99E-05	0,000194
QUICK RATIO	0,029984	0,006298	4,760791	2,036E-06	0,017634	0,042334	0,017634	0,042334
YEAR	-0,00672	0,000567	-11,8555	1,343E-31	-0,00783	-0,00561	-0,00783	-0,00561

All the models are significant at the 5% level for the F-statistic and the t-statistics of the variables' slopes. The Significance F is the p-value of the F-score (Richardson, 2015, p.84), shown in the ANOVA section of the table in the fifth column. If the p-value is less than the desired significance level, then the model is significant at that level (Wilson, Keating & Hodges, 2012, p.85). Therefore, with the Significance F being smaller than 0,05, the model is significant at the 5% level. The t-statistics of the slopes are higher than the critical value of the 5% level for a two-tailed t-test, the critical value being 2,447. This indicates significant slopes for all the variables.

The coefficient for Total Assets and Return on Assets is negative, indicating that the higher the variable's value, the lower the firm's annual volatility. Year has a negative coefficient as well, suggesting lower risk the later the year. Somewhat surprisingly, Total Asset Turnover's and Quick Ratio's coefficient is positive, suggesting that risk increases with either of the ratio's increase. Total Debt % Common Equity's positive coefficient makes sense from a logical standpoint: The more debt to common equity, the more risk.

The calculated Durbin-Watson statistic is 1,065471, indicating positive autocorrelation, but not in the strongest sense, as the value zero indicates the heaviest positive autocorrelation and the value of two indicates no autocorrelation. In this case, it is compensated by having Year as one variable. If Year is significant, autocorrelation exists and the variable treated it (Richardson, 2015, p.164).

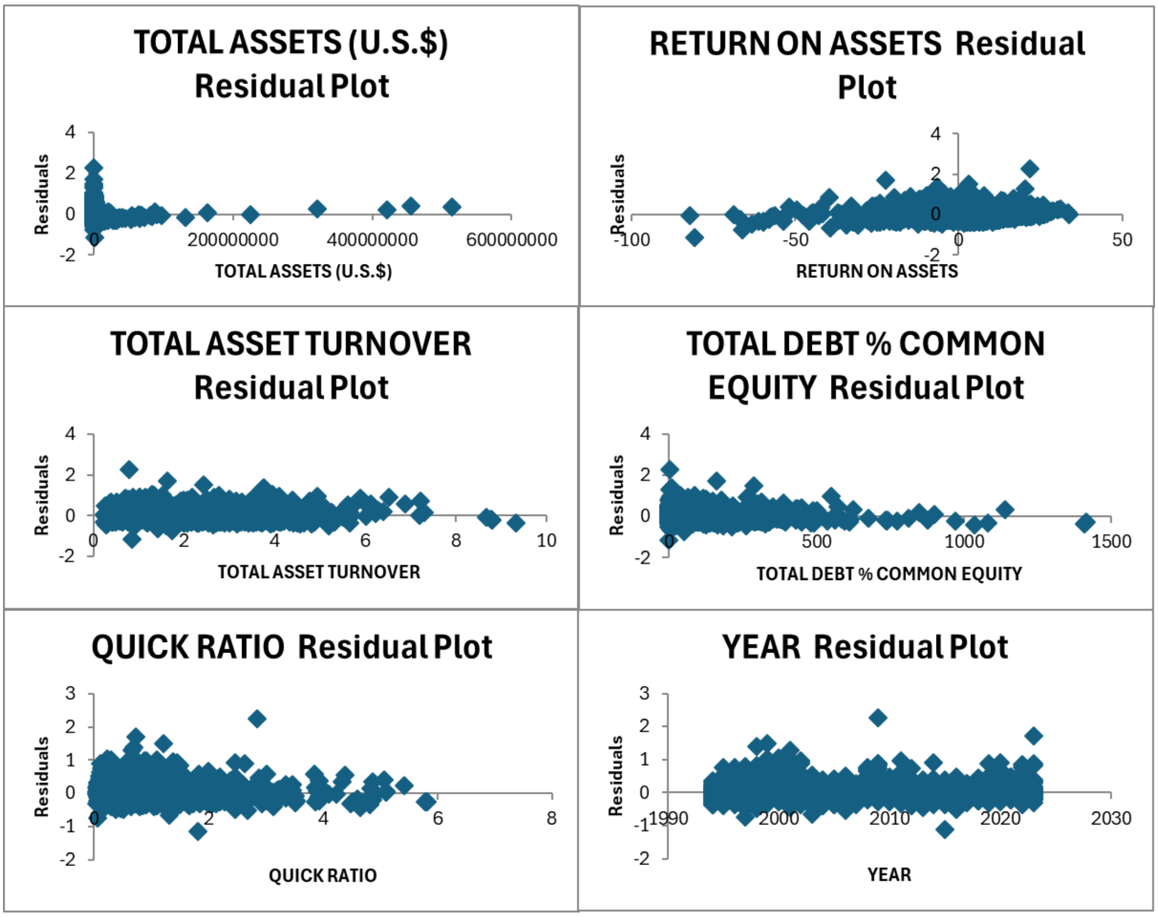

Figure 5. Residual plots for the Annual Std - All Independent Variables model.

8.2 Annual Std – Ratios

Table 13. Final regression model for Annual Std - Ratios.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,422651
R Square	0,178634
Adjusted R Square	0,177345
Standard Error	0,244351
Observations	2555

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	33,11265	8,278162	138,6458	2,5E-107
Residual	2550	152,2535	0,059707		
Total	2554	185,3662			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0,446871	0,013583	32,89934	3,6E-198	0,420236	0,473506	0,420236	0,473506
RETURN ON EQUITY - TOTAL (%)	-0,00382	0,00017	-22,4163	9,9E-102	-0,00415	-0,00348	-0,00415	-0,00348
TOTAL ASSET TURNOVER	0,030147	0,004476	6,735177	2,02E-11	0,02137	0,038924	0,02137	0,038924
TOTAL DEBT % COMMON EQUITY	0,000165	4,32E-05	3,82387	0,000135	8,05E-05	0,00025	8,05E-05	0,00025
QUICK RATIO	0,032946	0,006514	5,057799	4,54E-07	0,020173	0,045719	0,020173	0,045719

Return on Equity shows a negative coefficient like Return on Assets. The ratios show higher t-values compared to when Total Assets and Year were included except for Return on Equity, which was not included in the previous model. It shows to have a slightly lower t-value than ROA on the previous model. However, ROE and ROA show to be the most significant variables throughout the study regarding the t-statistic. The R^2 is reduced, but the model significance is higher than with Total Assets and Year included. The Durbin-Watson test for the residuals of this model outputs a value of 1,006963937, indicating positive autocorrelation.

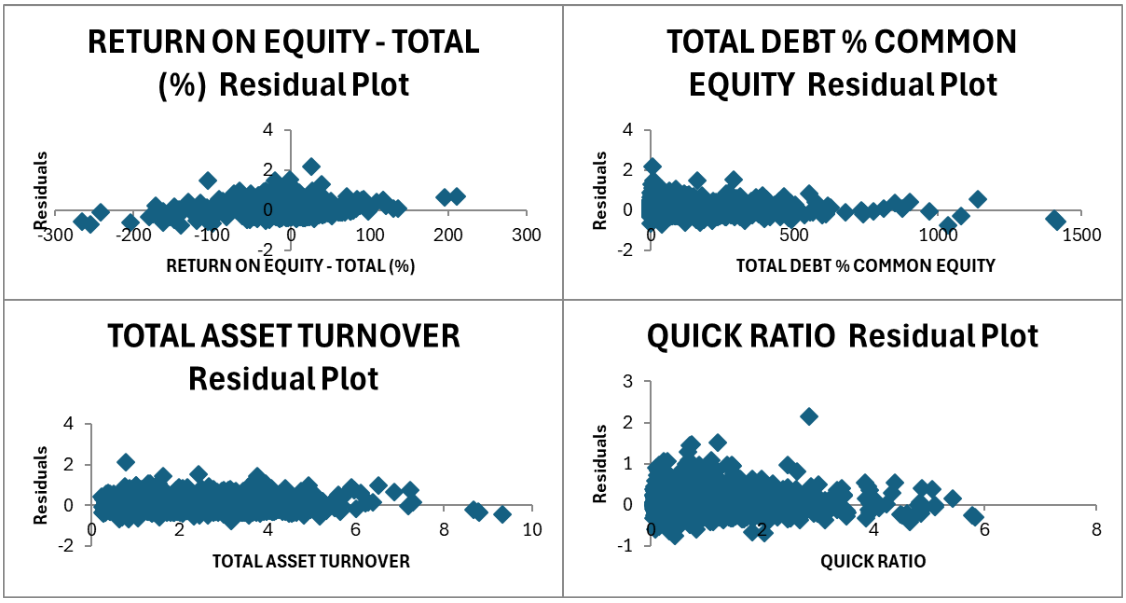

Figure 6. Residual plots for the Annual Std - Ratios.

8.3 Annual semidev – All Independent Variables

Table 14. Final regression model for Annual semidev - All Independent Variables.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,46315
R Square	0,214508
Adjusted R Square	0,212658
Standard Error	0,166594
Observations	2555

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	6	19,3116	3,2186	115,971	9,7E-130
Residual	2548	70,71587	0,027753		
Total	2554	90,02747			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	9,025908	0,803855	11,22828	1,37E-28	7,449633	10,60218	7,449633	10,60218
TOTAL ASSETS (U.S.$)	-5,4E-10	1,72E-10	-3,15476	0,001625	-8,8E-10	-2E-10	-8,8E-10	-2E-10
RETURN ON ASSETS	-0,00715	0,000317	-22,5216	1,4E-102	-0,00777	-0,00652	-0,00777	-0,00652
TOTAL ASSET TURNOVER	0,012131	0,003098	3,915947	9,24E-05	0,006057	0,018206	0,006057	0,018206
TOTAL DEBT % COMMON EQUITY	7,72E-05	2,96E-05	2,608652	0,009143	1,92E-05	0,000135	1,92E-05	0,000135
QUICK RATIO	0,020993	0,004445	4,722668	2,45E-06	0,012277	0,02971	0,012277	0,02971
YEAR	-0,00432	0,0004	-10,809	1,17E-26	-0,00511	-0,00354	-0,00511	-0,00354

Return on Assets is the most significant variable, with Year being the second most significant. Total Debt % Common Equity is barely significant at the 5% level but crosses the critical value. The Durbin-Watson test value for this model is 1,168008172, indicating positive autocorrelation but slightly less than in the previous models.

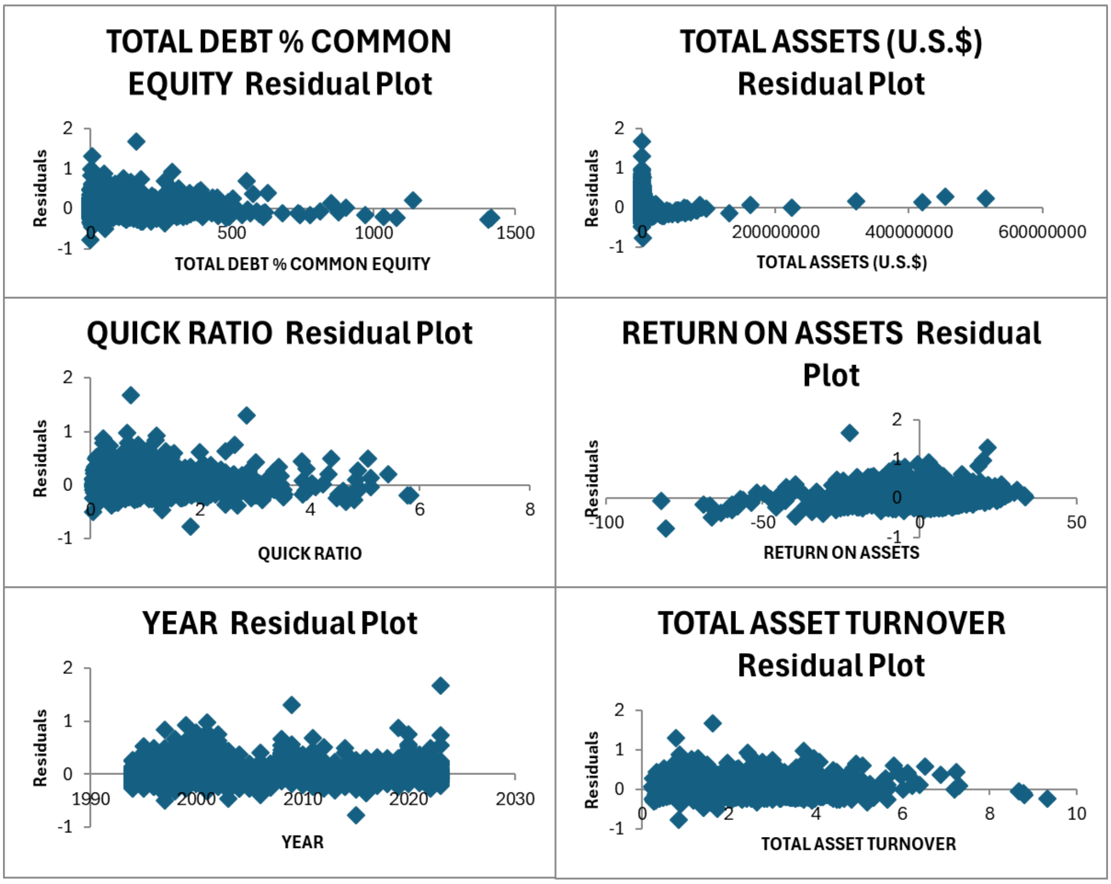

Figure 7. Residual plots for the independent variables in Annual semidev – All Independent Variables.

8.4 Annual semidev – Ratios

Table 15. Final regression model for Annual semidev - Ratios.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,41139
R Square	0,169242
Adjusted R Square	0,167939
Standard Error	0,17126
Observations	2555

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	15,23641	3,809104	129,8713	4,6E-101
Residual	2550	74,79106	0,02933		
Total	2554	90,02747			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0,315829	0,00952	33,17537	6,1E-201	0,297161	0,334496	0,297161	0,334496
RETURN ON EQUITY - TOTAL (%)	-0,0026	0,000119	-21,7438	2,62E-96	-0,00283	-0,00236	-0,00283	-0,00236
TOTAL ASSET TURNOVER	0,019053	0,003137	6,073233	1,44E-09	0,012901	0,025204	0,012901	0,025204
TOTAL DEBT % COMMON EQUITY	0,000114	3,03E-05	3,767262	0,000169	5,47E-05	0,000173	5,47E-05	0,000173
QUICK RATIO	0,022945	0,004565	5,025906	5,36E-07	0,013993	0,031898	0,013993	0,031898

For the regression model without Total Assets and Year, ROE, Total Asset Turnover, Total Debt % Common Equity and Quick Ratio are the significant ratios. ROE is the most significant ratio while Total Debt % Common Equity is the least significant while still crossing the 5% significance level. The Durbin-Watson value for this model is 1,105544139, indicating positive autocorrelation.

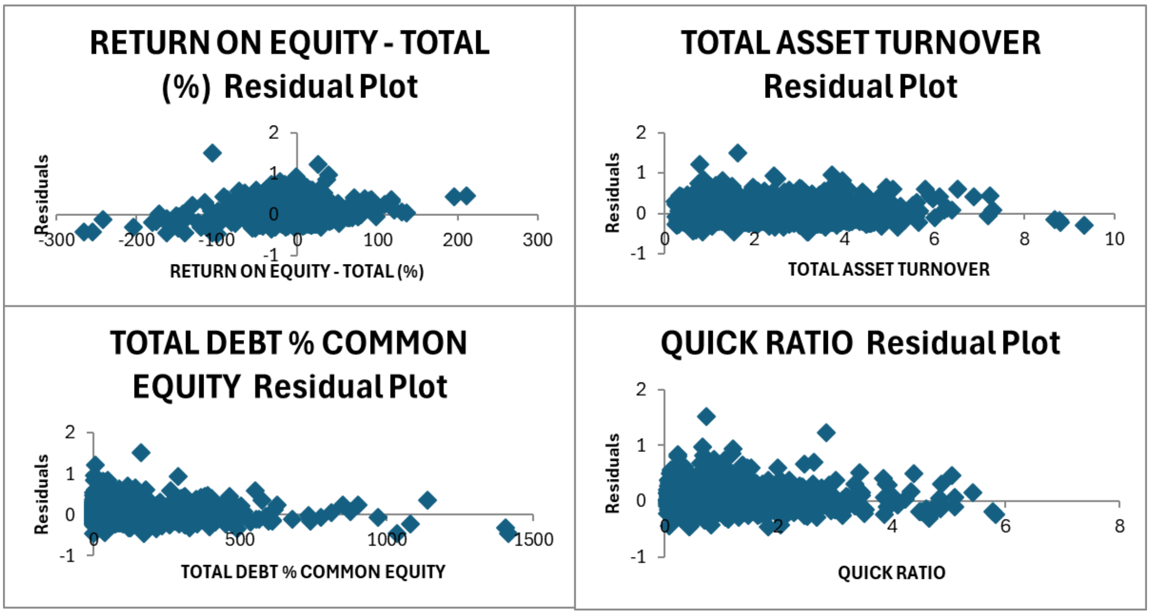

Figure 8. Residual plots for the independent variables in Annual semidev - Ratios.

8.5 Annual Std – Lagged Independent Variables

Table 16. Final regression model for Annual Std - Lagged Independent Variables.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,431894
R Square	0,186533
Adjusted R Square	0,184745
Standard Error	0,234775
Observations	2281

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	5	28,75419	5,750838	104,3341	2,4E-99
Residual	2275	125,3968	0,055119		
Total	2280	154,151			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	13,78523	1,2405	11,11264	5,64E-28	11,3526	16,21786	11,3526	16,21786

TOTAL ASSETS (U.S.$) LAG 1	-9,3E-10	2,87E-10	-3,23474	0,001235	-1,5E-09	-3,7E-10	-1,5E-09	-3,7E-10
RETURN ON ASSETS LAG 1	-0,00924	0,000501	-18,4232	9,3E-71	-0,01022	-0,00825	-0,01022	-0,00825
TOTAL ASSET TURNOVER LAG 1	0,018139	0,004659	3,893512	0,000102	0,009003	0,027275	0,009003	0,027275
QUICK RATIO LAG 1	0,02441	0,006771	3,604795	0,000319	0,011131	0,037688	0,011131	0,037688
YEAR LAG 1	-0,00662	0,000617	-10,726	3,22E-26	-0,00783	-0,00541	-0,00783	-0,00541

The R^2 is noticeably reduced compared to the model without the lag, reducing from 0,23418 to 0,18653. The F-score of the lagged model is also reduced. Return on Assets and Year are the most significant variables, with Total Assets surprisingly being the least significant. The Durbin-Watson test value for this model is 1,10317, indicating positive autocorrelation.

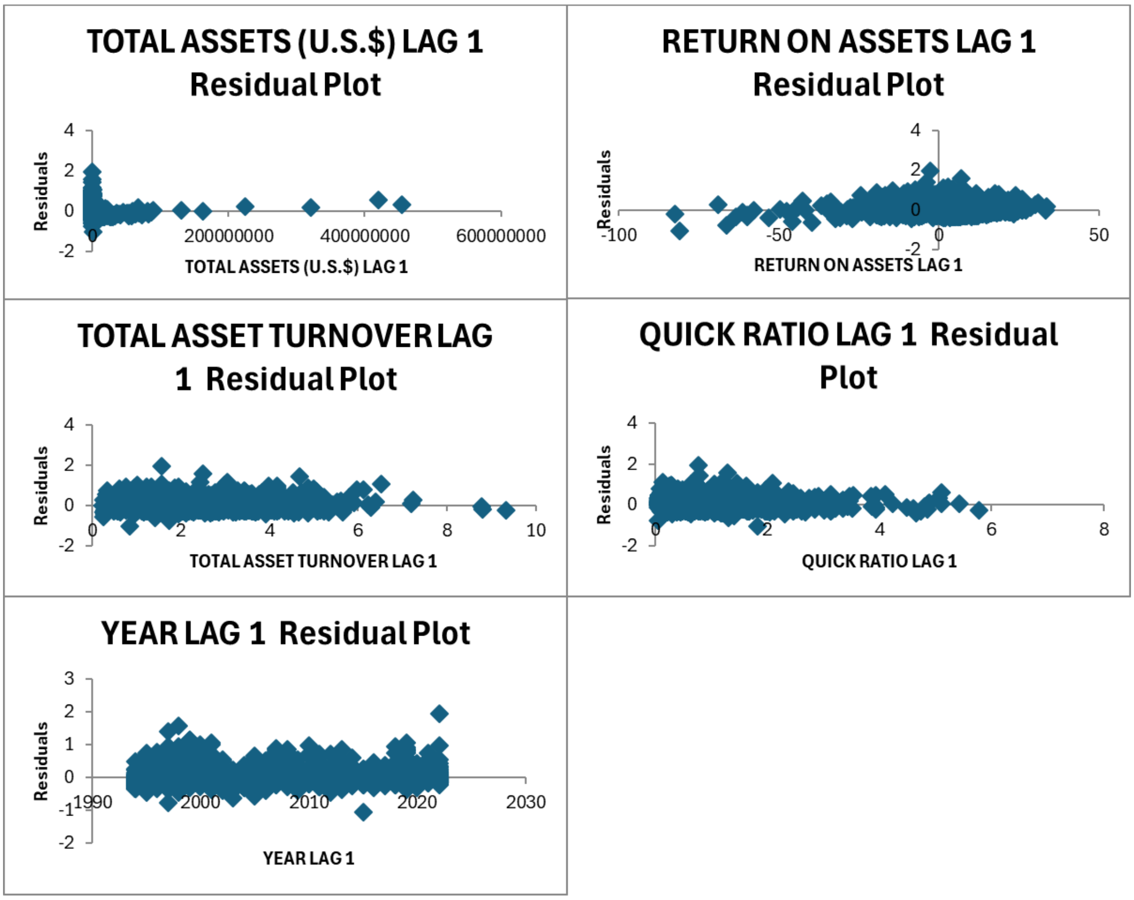

Figure 9. Residual plots for the independent variables in Annual Std - Lagged Independent Variables.

8.6 Annual Std – Lagged Ratios

Table 17. Final regression model for Annual Std - Lagged Ratios.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,345041
R Square	0,119053
Adjusted R Square	0,117505
Standard Error	0,244265
Observations	2281

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	18,3522	4,58805	76,89614	3,07E-61
Residual	2276	135,7988	0,059666		
Total	2280	154,151			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0,429457	0,016754	25,6328	1,6E-127	0,396602	0,462312	0,396602	0,462312
RETURN ON EQUITY - TOTAL (%) LAG 1	-0,00318	0,000194	-16,4194	2,41E-57	-0,00356	-0,0028	-0,00356	-0,0028
TOTAL ASSET TURNOVER LAG 1	0,026157	0,004755	5,501123	4,2E-08	0,016832	0,035481	0,016832	0,035481
TOTAL DEBT % TOTAL ASSETS LAG 1	0,000972	0,000322	3,018565	0,002568	0,00034	0,001603	0,00034	0,001603
CURRENT RATIO LAG 1	0,017773	0,00473	3,757214	0,000176	0,008497	0,027049	0,008497	0,027049

The R^2 is further reduced after taking out Total Assets and Year. The F-value 76,89 is lower than with the previous model, meaning that while the model is significant, it is less so than the previous model. Return on Equity is clearly the most significant variable, with Total Asset Turnover as the second most significant variable. The Durbin-Watson value for this regression model is 1,042374, indicating positive autocorrelation.

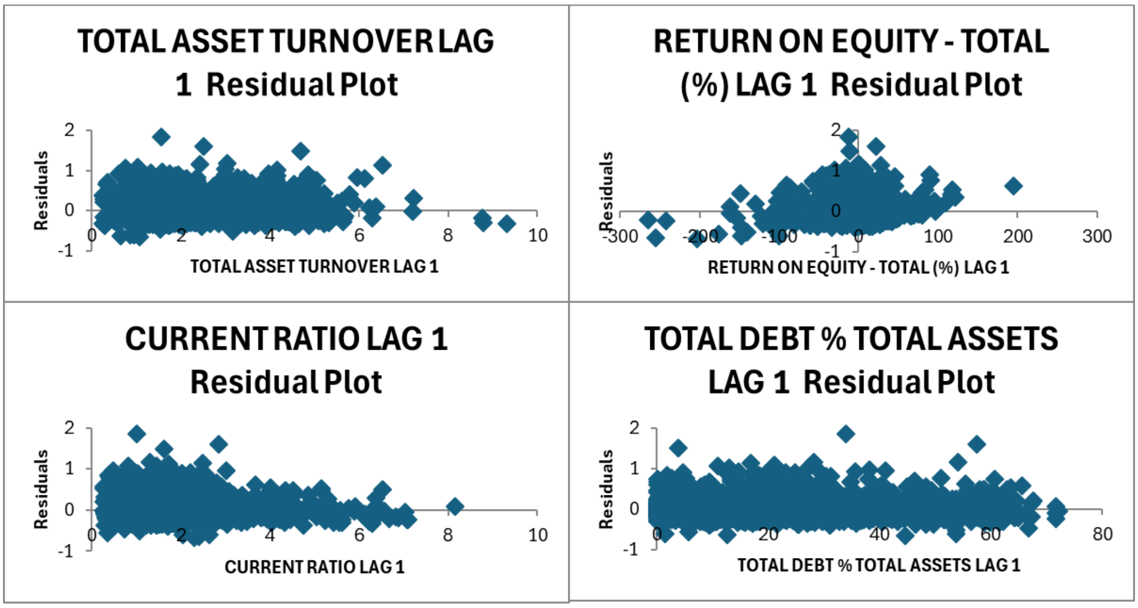

Figure 10. Residual plots for Annual Std - Lagged Ratios.

8.7 Annual semidev – Lagged Independent Variables

Table 18. Final regression model for Annual semidev - Lagged Independent Variables.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,398589
R Square	0,158873
Adjusted R Square	0,157024
Standard Error	0,167707
Observations	2281

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	5	12,08566	2,417132	85,94082	6,25E-83
Residual	2275	63,98559	0,028126		
Total	2280	76,07125			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	8,753969	0,886124	9,878943	1,45E-22	7,016273	10,49166	7,016273	10,49166
TOTAL ASSETS (U.S.$) LAG 1	-6,5E-10	2,05E-10	-3,17655	0,00151	-1,1E-09	-2,5E-10	-1,1E-09	-2,5E-10
RETURN ON ASSETS LAG 1	-0,00599	0,000358	-16,7267	2,53E-59	-0,00669	-0,00529	-0,00669	-0,00529
TOTAL ASSET TURNOVER LAG 1	0,010957	0,003328	3,29255	0,001008	0,004431	0,017483	0,004431	0,017483
QUICK RATIO LAG 1	0,018434	0,004837	3,81112	0,000142	0,008949	0,02792	0,008949	0,02792
YEAR LAG 1	-0,00419	0,000441	-9,49894	5,17E-21	-0,00505	-0,00332	-0,00505	-0,00332

The R^2 is slightly lower than with Annual Std as the dependent variable: This model has an R^2 of 0,1588, while the Annual Std – Lagged Independent Variables has an R^2 of 0,1865. Return on Assets Lag 1 is the most significant variable by far, and the runner-up is Year Lag 1. The Durbin-Watson value for this regression is 1,21817986, indicating positive autocorrelation but the least out of the models so far.

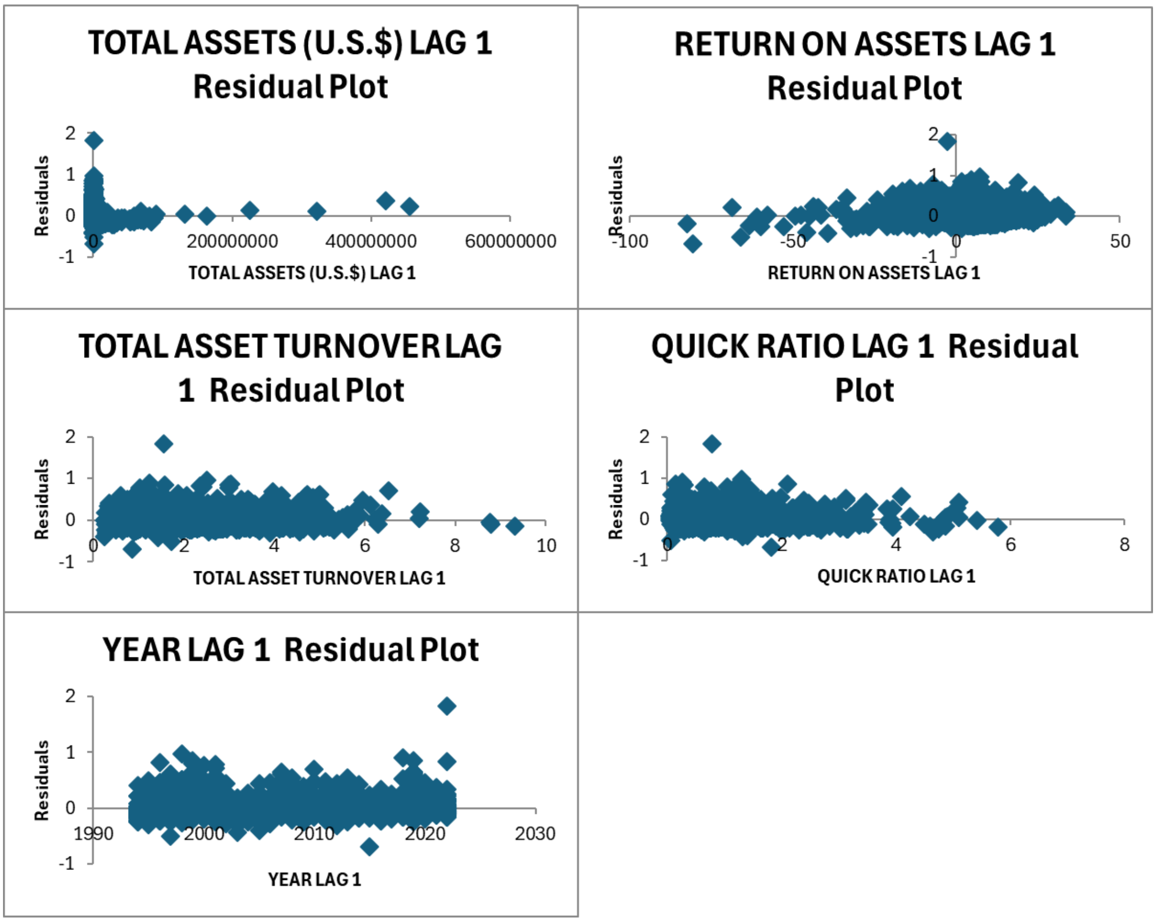

Figure 11. Residual plots for the independent variables in Annual semidev - Lagged Independent Variables.

8.8 Annual semidev – Lagged Ratios

Table 19. Final regression model for Annual semidev - Lagged Ratios.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,320519
R Square	0,102732
Adjusted R Square	0,101155
Standard Error	0,173175
Observations	2281

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	7,814974	1,953744	65,14743	3,14E-52
Residual	2276	68,25627	0,02999		
Total	2280	76,07125			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0,302499	0,011516	26,26883	4,6E-133	0,279917	0,325081	0,279917	0,325081
RETURN ON EQUITY - TOTAL (%) LAG 1	-0,00203	0,000137	-14,7909	2,46E-47	-0,0023	-0,00176	-0,0023	-0,00176
TOTAL ASSET TURNOVER LAG 1	0,017195	0,003399	5,058418	4,57E-07	0,010529	0,023861	0,010529	0,023861
TOTAL DEBT % TOTAL ASSETS LAG 1	0,000686	0,000229	2,997991	0,002747	0,000237	0,001135	0,000237	0,001135
QUICK RATIO LAG 1	0,022421	0,005037	4,450807	8,97E-06	0,012542	0,032299	0,012542	0,032299

The R^2 is the lowest out of all the models, following the same pattern as the Annual Std – Ratios regression. When Total Assets and Year are dropped, the R^2 suffers a drop. The significance of the model is still high, however. The Durbin-Watson value for this model is 1,158270655, indicating positive autocorrelation.

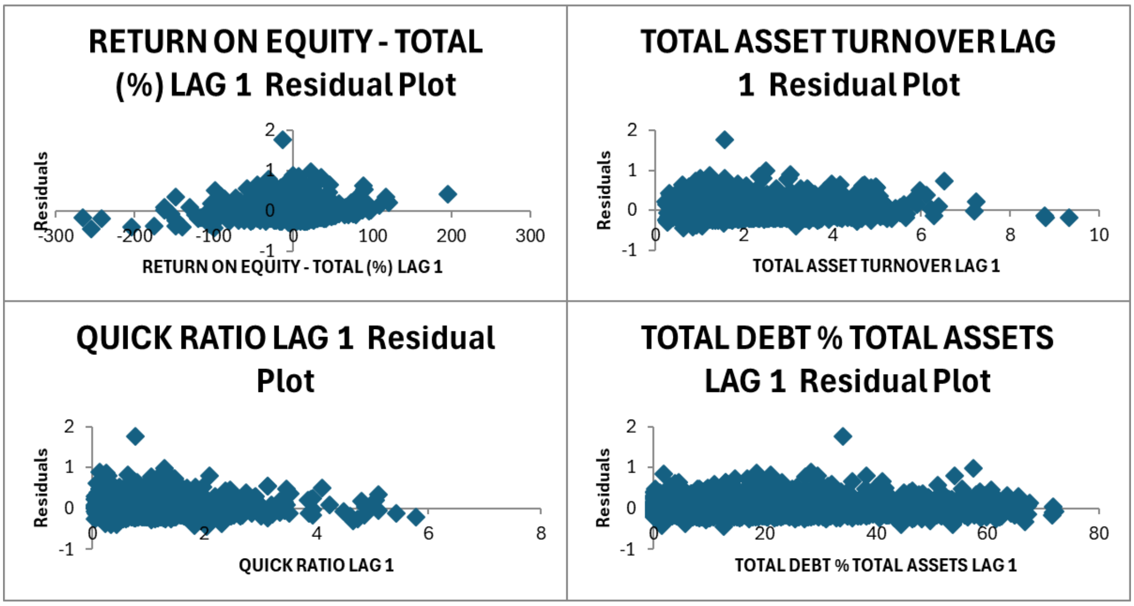

Figure 12. Residual plots for the independent variables in Annual semidev - Lagged Ratios.

8.9 Residual plots

The residual plots show that the equal variance- and independent assumptions are violated to a degree: For example, Return on Equity, Quick Ratio, Total Assets and Year show residual plots that are not evenly distributed. However, it could be said the residuals could be contained within a fixed, horizontal band except Total Assets, which shows a strong drop from zero onwards in the residuals, pointing to heteroskedasticity. Overall, the possibility of fitting residuals within a horizontal band indicates no alarming model defects (Montgomery, 2012, Chapter 4.2). On a further note, Quick Ratio and Total Debt % Common Equity residuals slightly thin out the further from zero they go. A seasonality trend can be observed in Year, as the residuals show a wave pattern. Most of the variables break the assumption of equal variances, but it should not affect the models drastically compared to multicollinearity or autocorrelation (Richardson, 2015, p.172).

8.10 Analysis

From the results we can derive that Return on Assets and Return on Equity are the strongest ratios, as they have the highest t-values. Furthermore, ROA and ROE are the only ratios with a negative coefficient: The higher the ratio, the lower the risk considering annual standard- or downside deviation. Other consistently significant ratios are found to be Total Asset Turnover, Total Debt % Common Equity, Total Debt % Total Assets and Quick Ratio. Total Asset Turnover is present in all the eight final models, ranking third in the highest recorded t-statistic in any of the models considering ratio performance. Quick Ratio has the fourth highest t-statistic, also being present in seven of the eight models. Total Debt % Common Equity and Total Debt % Total Assets cross the 5% significance level when one is present, however in some models they barely cross the significance level.

Total Debt % Common Equity and Total Debt % Total Assets naturally have a high degree of correlation, applying to Quick Ratio - Current Ratio as well as Return on Assets - Return on Equity. This high correlation always caused the other variable with high correlation to be dropped from the final model in the process. While all significant at the 5% level, no other ratio had as strong of a relationship with annual standard deviation and annual semi-deviation as did Return on Assets and Return on Equity.

For forecasting next year's volatility with the current year's independent variables, Return on Assets, Return on Equity, Quick Ratio, Total Asset Turnover and Total Debt % Total Assets make it to the final models. Interestingly, ROA is present when Total Assets and Year are in the model, and ROE is present when Total Assets and Year are not in the model. Total Asset Turnover and Quick Ratio are not as significant as ROA and ROE, but still cross the 5% significance level. For forecasting the next year's risk using financial ratios, the results in this study suggest that the best ratios from the eight tested, ranking by having the most presence to last (is included in the final models, t-statistic rank among the final ratios), are: Return on Assets, Return on Equity, Total Asset Turnover, Quick Ratio, Total Debt % Common Equity, Total Debt % Total Assets, and Current Ratio. Inventory Turnover didn't make it to any model, as it was quickly dropped in the process of regression runs because of a low t-statistic. Quick Ratio always had the higher t-statistic between Quick Ratio – Current Ratio, and they had high multicollinearity. Therefore, Current Ratio was dropped from nearly all models. The same applies to Total Debt % Common Equity – Total Debt % Total Assets in nearly all instances. Total Assets and Year are a good addition from an overall prediction model standpoint, for they can increase the R^2 and model significance (F-value). It makes sense from a theoretical standpoint as well, as the firm size and the year the data is from can affect volatility, for example Annual Std for the financial crisis year of 2008 is likely higher for firms than in 2015.

The final model for predicting next year's annual normal- and downside volatility using the current year's data is with Total Assets, Return on Assets, Total Asset Turnover, Quick Ratio and Year. With ratios only, for annual volatility the final model has Return on Equity, Total Asset Turnover, Total Debt % Total Assets and Current Ratio. The final model for predicting annual semi-deviation with ratios only is with Return on Equity, Total Asset Turnover, Total Debt % Total Assets and Quick Ratio.

Since ratios have a significant relationship with annual risk and a notable R^2 value, it is probable that investors form expectations based on financial ratios or the information that the ratios contain: For example, Return on Assets measures the net income of a firm to its total assets. Both are important to investors, so it is no surprise that a ratio like Return on Assets or Return on Equity have such a strong statistical significance with risk if investors form expectations partly based on the information included in the ratios.

The results in this study provide further support for the predictive capability of ratios. Instead of the random walk of prices described in Fama (1965), the prices likely show some sort of dependent movement, since ratios can predict price deviations to a degree. Autocorrelation is somewhat present in the study, suggesting correlated error terms. However, Fama (1965) does argue that there is no reason to expect that investors have completely independent expectations, which may translate to some dependency in price movement. The results in this study also support the information generation described in Fama (1965): Good news is likely followed by good news. If the previous years' ratios can explain around 10-12% of the next year's standard- and semi-deviation, the information generation seems to not be completely independent.

If ratios can consistently provide support as a part of a model for future volatility, they could open potential investing opportunities that the market has not detected. If the ratios give clues of the upcoming year's volatility, this should affect the valuation of the asset and investor behavior. However, if all investors are using the information contents of the ratios, the potential investing opportunity is already gone, as the future risk would already be accounted for by the market. Furthermore, if ratios can forecast risk and even returns, this should alleviate the arbitrageur's problems described in limits of arbitrage (Shleifer and Vishny, 1997). If the arbitrageur can obtain more information than other market participants on the future risk levels, the arbitrageur is more aware of the fundamental risk of the asset than others. By knowing more, the arbitrageur would also be aware of higher potential profits than others realize. This information may assist in selling an overpriced asset short, for example. While not riskless, the arbitrageur recognizes more of the potential risk level due to an accurate volatility forecast involving ratios.

From the behavioral finance's perspective, specifically the prospect theory discussed in Barberis and Thaler (2003), knowing more of the future risk level of an asset would probably affect the investor's evaluation of potential gains and losses. Utilizing ratios could also show potential irrational investor behavior patterns through trend forecasts in asset risk level.

9 Conclusion

The purpose of this thesis is to study whether financial ratios have any relationship with annual standard- and downside deviation (semi-deviation). Furthermore, it is studied whether the current year's ratios have any relationship with the next year's standard- and semi-deviation, and if there is a possibility to build a statistically significant prediction model.

Rational investors are always looking for ways to turn a profit with minimal risk. Financial ratios show evidence that they have predicting capabilities (Beaver, 1966; Abarbanell and Bushee, 1998; Altman, 1968). This shouldn't be possible in an efficient market. If prices fully reflected all available information, they would reflect all the information contained in financial ratios. It could also be that mispricing persists, if rational investors are not utilizing the opportunity for abnormal returns using financial ratios to remove the opportunity.

This study examines ten variables, of which eight are financial ratios. Total assets and the year are also included in four regressions to see whether firm size and period affect risk, and to compensate for autocorrelation. The eight ratios examined are Return on Equity, Return on Assets, Total Asset Turnover, Total Debt % Common Equity, Total Debt % Total Assets, Quick Ratio, Current Ratio, and Inventory Turnover.

The results indicate that there is a significant relationship with most of the financial ratios considering annual standard- and semi-deviation. Return on Equity and Return on Assets have the most significant relationship by a considerable margin, and they are the only ratios with negative coefficients. This indicates that the higher either ratio's value is, the lower the risk of the stock. Based on the results, for all except Inventory Turnover the null hypotheses of the study can be rejected that there is no ratio with a significant relationship regarding standard- or semi-deviation.

Regressing all the ratios' values with the same year's risk shows that there is a significant relationship at the 5% level between realized annual standard- and semi-deviation and the ratio values for the same year. The final regression model shows Return on Assets, Total Asset Turnover, Total Debt % Common Equity and Quick Ratio to be the significant ratios when Total Assets and Year are included as well. When Total Assets and Year are omitted and the regression model is based on ratios only, the final model has Return on Equity, Total Asset Turnover, Total Debt % Common Equity and Quick Ratio. The R^2 of the models are 0,214 and 0,234 when Total Assets and Year are included, and 0,178 and 0,169 when only ratios are regressed. The R^2 is not very high, but still surprisingly high considering that one can explain 17% of the current year's risk with only a few ratios.

Regressing the current year's variable values and the next year's annual standard- and semi-deviation shows if the independent variables have any predicting capabilities. The results show lower model significance and R^2 but are still significant at the 5% level. For predicting next year's annual normal- and semi-deviation, the final model has Total Assets, Return on Assets, Total Asset Turnover, Quick Ratio and Year. With ratios only, for annual standard deviation the final model has Return on Equity, Total Asset Turnover, Total Debt % Total Assets and Current Ratio. The final model for predicting annual semi-deviation with ratios only is with Return on Equity, Total Asset Turnover, Total Debt % Total Assets and Quick Ratio. With Total Assets and Year included, the R^2 for Annual Std – Lagged Independent Variables is 0,186. The R^2 for the corresponding Annual semidev – Lagged Independent Variables model is 0,159. For ratios only, the corresponding R^2 is 0,119 and 0,103, respectively.

In conclusion, seven of the eight financial ratios can be found to have a significant relationship in at least one of the eight final models. Based on the results, the null hypotheses of the study can be rejected. Inventory Turnover is the only ratio without a statistically meaningful relationship regarding annual standard- and downside deviation. Financial ratios in the final models alone can explain 17,8% of the same year's standard deviation, and 16,9% of the same year's semi-deviation. For next year's standard deviation, financial ratios in the final models can explain 11,9%, and 10,3% for next year's semi-deviation. The addition of total assets and year in the models add to the R^2 significantly, from 4,5 to 6,7%.

It would be interesting to see further research on the relationship with financial ratios and risk, and whether there are more ratios that are as significant as Return on Assets and Return on Equity. The reliability and robustness of ratios predicting risk is also uncertain, which could be studied further through a trading strategy. As ratios are easily accessible, they could be great tools for all kinds of investors seeking potential warning signs on the stocks in their portfolio regarding risk level. This allows pre-emptive action: If the warning signs are there, the investor can sell the asset before losses are realized.

9.1 Limitations of the study

This study suffers from a few limitations. The equal time step assumption of regression (Richardson, 2015, p.164−165) is violated with year gaps that are of different size between stock tickers, as for example Ticker 1 may have acceptable observations from 1999 to 2002, while Ticker 2 has acceptable observations from 2016 to 2018. This causes unequal time steps when all observations are arranged in a sequence: 1999, 2000, 2001, 2002, 2016, 2018 and so forth. The jump from 2002 to 2016 violates the equal time step assumption.

Another violation of regression assumptions is slight autocorrelation, with the Durbin-Watson values revolving around 1. This indicates positive autocorrelation, meaning that the errors are not completely independent (Richardson, 2015, p.160). This may skew the regression results. Furthermore, heteroskedasticity is present when inspecting the residual plots of the regressions. The residuals are not always equally distributed nor random. This may affect the regression results as well, compared to having data that has no heteroskedasticity.

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