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on the topic: **"THE EFFECTIVENESS OF FUNDAMENTAL ANALYSIS IN FORECASTING STOCK RETURNS IN TECHNOLOGY SECTOR**

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INTRODUCTION

The efficiency of the stock markets is the central question of the financial academic research of the last few decades. The ability of fundamental or technical analysis to predict stock returns is often an instrument used to test whether stock markets are efficient, however, the results of the tests are often contradicting and no universal agreement on the question has yet been reached.

A highly recognized paper by Eugen Fama published in 1970 called "Efficient Capital Markets" argued the extreme efficiency of the stock markets which incorporate any new pieces of news too fast for the fundamental or technical analysis to have any predictive power. Following this logic, a manually selected portfolio would not be able to generate returns greater than a randomly selected portfolio with comparable risk [32].

Despite this, several papers appeared after the 1960s examining various anomalies in stock returns, including the size effect and overperformance of 'value' stocks. Not all papers necessarily argued that these anomalies signal the market's inefficiency and often tried to incorporate these extra factors into the CAPM model.

By the start of the 21st century, the dominance of the efficient market hypothesis decreased as more researchers started examining strategies that would allow for generating excessive risk-adjusted returns and explored the psychological and behavioral patterns which put the rationality of investors in doubt.

Nevertheless, Malkiel, the author of the famous book titled 'A Random Walk Down Wall Street', in his paper still argues that the stock market is much more efficient and less predictable than some studies of the early 2000s argued [32]. The author acknowledges the excessively recorded anomalies in the stock price movement, however, concludes that stock markets are still efficient when efficiency is defined as investors' inability to generate 'above-average returns without accepting the above-average risks.

Although it is difficult to argue against the existence of mispricing of stocks and the effect of behavioral factors in the stock market, the long-term exploitability of any patterns is very questionable. A confirmed predictive pattern would allow for generating abnormal returns and doing a search for a strong predictive model or pattern with a focus on actively managed funds. However, even with all the resources and skilled analysts, the outperformance of the actively managed funds is still debatable.

With this said Malkiel's research does not aim to attack the efficient market hypothesis but rather accepts its presence in the long run and assumes the possibility to exploit mispricing anomalies in the short run. This study focuses on the exploration of the relationship between key fundamentals and stock returns specifically for big tech companies. The construction of a ready-to-use model to assist investment decisions is not in the scope of this research, however, the study of the relationships is an important step toward the development of industry-specific quality-driven valuation models.

The paper is partially based on fundamental and well-recorded findings about general relations between key fundamentals and stock returns. At the same time, modern valuation strategies are kept in mind and incorporated into the research design. The research zooms into a relatively young tech industry, exploring if fundamental relationships previously recorded for the broad market can generate meaningful returns for companies in the tech industry. The research also uses data from a fairly recent period making it interesting to observe if previously recorded relationships still hold. For example, multiple researchers reported that the size effect disappeared from the recent stock market data. The study of the relationship is conducted with the prospect of applying the findings to create an industry-specific quality-driven valuation strategy.

Panel data is used for this analysis instead of a portfolio approach. As Bauer et al. state, the construction of portfolios is a popular method of academic research used to evaluate the predictive power of various factors on stock returns [12]. The portfolio approach was used in many of the fundamental works of the 20th century, including that of Fama and French in 1996 [20]. The idea of the portfolio approach is to sort the stocks by the explored

characteristic, construct several portfolios based on the value of the characteristic and then compare the returns over time.

The portfolio approach can yield high-quality results when the number of factors explored is limited to 1 or 2, however, as the number of factors grows the construction of portfolios becomes too resourceful. There is also an issue of the industry effect which is difficult to address when using the portfolio approach. One of the solutions is the use of panel data which enables the researchers to explore the effect of multiple characteristics and makes it possible to control for individual or time-related factors. Still, the portfolio approach is more likely to produce robust results. Portfolios of stocks are more balanced than individual stocks, they are less noisy, and the outliers don't have much impact on the results.

One of the questions of the work of Bauer et al. from 2004 that is particularly important for this research is whether industries play a role important enough to construct industry-specific models [12]. The findings suggest industry-specific effects to be significant and provide some reasoning for further research among certain industries.

The tech industry is the focus of this research because of the challenges in valuation it presents. A high level of uncertainty and risk is also associated with high-tech companies as was demonstrated by the dot com crisis in the 2000s. The companies whose future earnings usually solely depend on the ability to leverage their technology can often be overvalued by investors as these technologies may be too complex for an average investor to understand. The impact of new technology can also be difficult to assess as some may arise at a time when the demand is not yet sufficient. A fast pace of technological advancement is the other challenge in tech companies' valuation. Competitors' superior technological advancement may tear down years of R&D and destroy expectations of future earnings growth.

The fast pace and intensity of these technological updates make it difficult for a non-technical investor to assess the impact of the new information on the company's future earnings. It becomes even more difficult when technology becomes 'viral' and gains massive coverage thanks to the modern media. A recent example is the overwhelming amount of

coverage received by Open AI and their Chat GPT model. It demonstrates how fast technology can attract public attention and how intensive the competition and technological advancement are in the high-tech market. Soon after the Chat GPT 3 was publicly launched Google announced their new AI chatbot. A few months later Open AI's model was updated to Chat GPT-4. A model took a huge leap from the 3rd version not leaving a previous model a chance to compete with it.

The complicated nature of the technology, its novelty, the intensity of updates, and social media 'hype' raises questions as to whether the impact of the new information on the companies' future earnings is correctly reflected in the price. With the assumption that price volatility in the industry is often subject to the subjective interpretation of new information pieces and knowledge of specific characteristics of tech companies' fundamental data, this research aims to explore whether key fundamentals still have any predictive power in the sector.

This study doesn't present enough evidence to reject the efficient market hypothesis, however, it challenges it by exploring over or underreaction to the new information in the industry. Although the paper focuses more on exploring the existence of the relationships its theoretical reasoning is based on the theory proposed by Abarbanell and Bushee in 1998 [2] and on the work of French and Fama in 1992 [18].

This paper aims to explore whether the fundamentals of tech companies may be accurate predictors of future earnings. The reasoning proposed by Abarbanell and Bushee is that the stock market may fail to accurately react to fundamental information immediately but instead incorporates it with some time lag [2]. Another explanation is provided by French and Fama, who viewed that risk may be multidimensional, and from this perspective, the null hypothesis isn't rejected either [18].

Topic relevance: The fast pace of technological advancement and the complicated nature of the information that may impact expectations about future earnings make the valuation of companies in the technology sector challenging. Due to significant differences, the relationships in the tech sector may also differ from the general market. This is a rationale

for exploring a possible creation of a sector-specific model or strategy. Multiple works analyzing single industries have been published, however, none focused on the technology sector.

Goal: This work aims to analyze the relationships between key fundamental ratios and stock returns of technological companies from the NASDAQ 100 Technology Sector Index for the period between 2012 and 2022. The return with a one-quarter lag is regressed against six fundamental ratios (book-to-market ratio, price-to-earnings ratio, return on assets, leverage ratio, current ratio, and earnings per share). Panel data is used, and the best-fitting model is selected. The results are analyzed, explained, and compared to findings in previously published research.

Object: The paper focuses on the correlations between one-quarter ahead returns of tech companies and their fundamental ratios.

Research Subject: Six fundamental ratios and average quarterly returns with a one-period lag for 31 tech companies during 2012-2022 are the subjects of this research.

Key words: fundamental analysis, stock market, the technology sector, fundamental ratios, abnormal returns.

CHAPTER 1. LITERATURE REVIEW

1.1. Definition of fundamental analysis

Effectively predicting future movements of stock prices is the all-time goal of most investors. Several approaches and strategies with various degrees of theoretic reasoning and meaningfulness have been historically utilized to achieve excess returns. The two most commonly used approaches are technical or "chartist" theories and the theory of fundamental or intrinsic value analysis [19].

Patterns in past stock price movements lie at the core of the technical analysis. Professionals who utilize this approach analyze price and trading volume charts and graphs in search of some "clues" that would allow them to increase future potential gains. The basic assumption behind this approach is that theory repeats itself and price movement patterns will reoccur [19].

The key assumption behind fundamental analysis is that all securities have an intrinsic value that depends on their earning potential. The earning potential of a security depends on various internal and external factors which affect a company including management, competition, prospects for growth, inflation, etc. The intrinsic value of a security is its fair price; however, fundamental analysis professionals believe that the current price can deviate from its intrinsic value.

Fundamental and technical analysis are different at their core. As Malkiel states in "A Random Walk Down Wall Street" first published in 1973, those who use technical analysis believe that the stock market is more psychological than rational while fundamental analysis advocates argue that the market is mostly logical and only 10% of price movement is attributed to psychological factors [34].

One interesting example of fundamental versus technical analysis comparison is the work of Avramov, Kaplanski, and Levy [5] in which data from the TV show "Talking Numbers" was used to analyze and compare the performance of technical and fundamental analysis in predicting stock returns. A total of 1599 investment recommendations were used, each including a fundamental and technical approach, and results suggested that technical analysis was able to predict results up to one year. The excess return on technical recommendations was reported at 5.4% while for fundamental analysis it was around 1.5%. Based on the results authors report the inability of the fundamental analysis to predict future stock returns and the relatively strong performance of technical analysis-based recommendations for individual stocks over a short-term period.

As both fundamental and technical analysis challenge the efficient market hypothesis it is natural that they are being challenged by theories that support the efficiency of the markets. One prominent example is the theory of Random Walks. The theory assumes markets are efficient, however, adds a factor of uncertainty present in the real world which makes it difficult or almost impossible to estimate intrinsic value perfectly. Due to some disagreement on the intrinsic value between the investors, the price will wander randomly around its intrinsic value. If a predictive and systematic pattern is spotted, the actions of many intelligent investors and analysts who spotted it will eventually neutralize any opportunities for excess gains. And when the intrinsic value itself changes due to some news, the theory states that the time lag and the nature of the price adjustment (over- or under-adjustment) are themselves random [19].

The theory of Random Walks states that past price movements have no predictive power for future price movements, and they are as good as a series of cumulated random numbers [19]. The challenge that the Random Walks theory presents for the technical analysis is straightforward as it denies the hypothesis it is constructed upon. The implications for fundamental analysis are not as radical. If markets are efficient in a way that the theory suggests then the only opportunity to gain from fundamental analysis occurs when an investor possesses some information that is not fully reflected in the price or is unknown to

the market. In other cases, the predictability is as good as a random selection of stocks with comparable risk [19].

The validity of either of the theories goes as far as the body and plausibility of findings that support it. In the conclusion of Fama's 'Random Walks in Stock Market Prices' paper published in 1995, it is stated that if Random Walks efficiency is assumed to support the fundamental analysis theory it needs to be proven that complicated selecting procedures are more profitable than random selection of securities [19].

In the next section, an evolution of fundamental analysis and its approaches to stock price prediction will be shortly summarized to briefly describe the theoretical body upon which this research is based.

1.2. Fundamental analysis research before 2000

In the late 20th century, many well-recognized and widely cited papers were published that examined some anomalies in the stock price returns that were not captured by the Capital Asset Pricing Model. The presence of these effects rose a question as to what extent their predictive power can be attributed to unrecorded risk factors. This part of the paper presents key findings from some of the well-recognized fundamental analysis papers in the second half of the 20th century.

In a 1981 paper, Banz examined the 'size effect' based on the data for NYSE common stock and found that a relationship between firms' market value and their average stock returns exists and firms with smaller market capitalization tend to earn higher risk-adjusted returns than bigger firms. This suggested that CAPM is misspecified [8].

Basu in 1983 explored the relationship between stock returns, firm size, and E/P documenting that a positive relationship between E/P and risk-adjusted returns exists if the size is controlled for [11]. However, he also discovered that while smaller companies tend to yield higher average returns than larger firms, the relationship tends to disappear when E/P is included in the equation. Previously Basu [9,10] recorded that stocks with high

earnings yield (E/P) tend to have higher average returns. Similar results were obtained by Banz in 1981 based on the analysis of NYSE common stock. Basu addresses the study conducted by Reinganum in 1981 which stated that E/P and size are likely to represent the same factor of risk not recorded in the CAPM, E/P is likely to be a proxy for size and the predictive power should be associated with the size [8]. This, however, appears contrary to the findings of Ball in 1978, who viewed E/P as a "direct proxy for expected returns" [6]. Basu in 1983 used the portfolio approach to address this question and understand the role of E/P and size in predicting stock returns and concluded that at least for the data that the research was conducted for size effect seems to disappear when E/P differences are accounted for [11].

Fama and French analyzed the relationship between variation in stock returns and two factors: size and book-to-market equity [18]. The research arose from the limitations of the asset-pricing model, like the size effect recorded by Banz [8], a positive relation between leverage and average return reported by Bhandari in 1988 [13], and positive relation of book-to-market equity to average stock returns. Fama and French [18] performed tests including β, size, E/P, leverage, and book-to-market equity. Tests did not support the prediction that a positive relation between market β and expected returns exists, however, a strong relationship exists between stock returns and size, leverage, E/P, and book-to-market equity. The relation between size and average return is negative, while book-to-market equity and return have a positive relationship. Fama and French document that these two variables also seem to absorb the effect of E/P and leverage, concluding that most of the relation between E/P and average stock returns is due to a positive correlation between E/P and ln(BE/ME). The explanatory power of E/P diminishes when the size and book-to-market equity is added to the model. Additionally, a negative correlation between size and book-to-market equity was recorded.

Abarbanell and Bushee [2] continued their previous research and studies conducted by Lev and Thiagarajan in 1993 [31] and explored whether the stock market fails to immediately reflect all the publicly available information - a key idea upon which all

fundamental analysis strategies are built. The authors introduced several signals, which reflected “changes in inventories, accounts receivables, gross margins, selling expenses, capital expenditures, effective tax rates, inventory methods, audit qualifications, and labor force sales productivity” [2, p.19] to construct portfolios that generated 13.2 percent 12-month cumulative abnormal returns. Their key assumption is that stock price adjustment to the new information is not complete right after the announcement and analysts' revisions of earnings forecasts often underreact to changes in signals. This assumption arose from previously conducted research by Abarbanell and Bushee, where they found that analysts tend to undervalue the information about price adjustments from the signals. This study is valuable in a way that it provides some explanation of how the publishing of a firm’s accounting information is incorporated into the price and provides justification for the use of a one-quarter lag in this research.

Greig in 1992 [25] in his research addressed the work of Ou and Penman in 1989 [36], which was also referenced by Abarbanell and Bushee [2]. Ou and Penman argue that stock prices often deviate from their intrinsic values and return to them only after some time. They state that by analyzing publicly available accounting information and applying fundamental analysis abnormal stock returns can be generated. They construct an aggregate value named Pr, which indicates the probability of the firm’s earnings increasing over one year. Ou and Penman [36] summarized that their findings suggested that fundamental analysis identifies equity values not yet reflected in the stock price. Greig [25] argues that the Pr value created by Ou and Penman [36] identifies the expected returns and not the abnormal returns by acting as a yield-surrogate capturing factors related to yield and size. Although Ou and Penman conducted tests and concluded that the abnormal returns are not associated with risk factors when the value of size is added to the model the previously captured relationship becomes insignificant. Greig suggested that the Pr value is just a proxy for firm size and the research recorded a well-known size effect instead of producing new evidence of firms’ mispricing.

1.3. Fundamental analysis research after 2000

Research in the early 2000s started aiming for a strategy that would allow gaining risk-adjusted excess returns. Some strategies seemed to allow excess returns to be gained and provide researchers with enough confidence to challenge the efficient market hypothesis. Panel data started being used more often and in recent years more research papers utilizing machine learning algorithms appeared.

In a 2010 paper Richardson et al. summarized and reviewed recent research dedicated to accounting anomalies and fundamental analysis focused on predicting future stock returns and published after the year 2000. The paper suggests that research of fundamental analysis should follow an approach of maintaining the null hypothesis of stock market efficiency as it is viewed as one able to produce the most robust results. Based on the conducted survey the researchers divide academic papers into four categories: “Fundamental Analysis, Accruals Anomaly, Underreaction to Accounting Information (also called a post-earnings announcement drift), and Pricing Multiples and Value Anomaly” [40]. The fundamental academic papers from each of the four categories cited by Richardson et al. [40] are also briefly covered in this paper.

Richardson et al. focus on a list of characteristics that they believe differentiate quality research dedicated to the use of fundamental analysis for stock returns prediction. The authors state 6 characteristics among which are the sound alternative hypotheses and theoretical reasoning behind the relationships studied, treatment of risk and transaction costs, and incorporation of non-price tests to confirm that the relationship demonstrates mispricing and no extra risk [40].

The authors also make an important argument that the studies exploring the relationship between the fundamentals and stock returns should have a solid and theoretically based reasoning on why the stock market fails to incorporate this information in a timely matter. The existence of a relationship between a firm’s fundamentals and its stock returns is not enough to reject the hypothesis of market efficiency. The works included

in this section of the literature review showcase different approaches to fundamental analysis research.

In a study published in 2000, Piotroski develops a system of financial signals for further analysis of high book-to-market stocks. By using historic financial data and nine indicators he can predict winners and losers among high book-to-market firms creating a portfolio that generated a 23% annual return between 1976 and 1996 [39]. According to Li and Mohanram, the nine signals he uses are: return on assets (ROA), cash flow from operations (CFO), change in ROA (ΔROA), accrual, change in leverage (ΔLEVER), change in liquidity (ΔLIQUID), equity offering (EQ_OFFER), change in gross margin (ΔMARGIN), and change in asset turnover ratio (ΔTURN) [32].

Li and Mohanram compare the results of two different fundamental analysis strategies, those that are based on quantity against strategies based on value [32]. They find that all four examined models produce significant positive returns while their combination produces the best results. The value approach suggests searching for undervalued stocks, while the quality approach searches for firms the accounting fundamentals of which function as signals and suggest high future earnings. The authors note that both approaches have certain limitations, for example, the value-driven approach can only be used for companies whose future cash flows can be estimated. The authors evaluate four following models: FSCORE from Piotroski [39] and GSCORE from Mohanram [35] for quality-driven strategies and the V/P strategy from Frankel and Lee [22] and the PEG strategy for value-driven strategies. All four strategies generated meaningful hedge returns but the authors were able to increase them significantly by combining value and quality-driven strategies in one model. The authors suggest that this new model would indicate “affordable quality firms”.

The nine signals that Li and Mohanram use can be split up into three categories: profitability, financial leverage or liquidity, and operating efficiency [32]. The authors define each of the nine signals as either good or bad and then attribute indicator values of 1 to good values of stocks and 0 to bad values. The aggregate signal measure is a sum of all 9 signals, which are either 1 or 0. The aggregate measure indicates how strong the financial position

of a firm is and it varies between 0 and 9. Based on the authors' assumption a higher aggregate measure would indicate firms with higher future earnings. It should be noted, that the authors built the model based on the assumption that high book-to-market firms are financially distressed. Another significant limitation is that some significant data can be lost due to the use of binary variables, still, the results demonstrate that the chosen fundamentals can produce significant positive results.

Mohanram [35] uses a similar approach with 8 signals and values of 1 or 0 attributed to firms based on their values, however, his approach compares firms' values to their peers and attributes a value of 1 if a positive signal's value is greater than the industry median and vise versa. When using these two quality-driven strategies Li and Mohanram [32] turn the binary values into continuous distributions between 0 and 1.

Wafi, Hassan, and Mabrouk summarize the most popular value-driven approaches, which aim to determine the fair or intrinsic value of stocks [44]. In concept, the excess returns are generated by investing in the undervalued stocks and waiting till the market adjusts and their price reaches their intrinsic value. The most popular models are Dividend Discount Model, various models which rely on multipliers, Discounted Cash Flow Model, and Residual Income Valuation Model. For instance, the previously mentioned V/P model uses the Residual Income Valuation Model while the PEG model uses the forward P/E ratio.

Anjani and Syarif use an approach similar to this study by analyzing the effect of fundamental analysis on stock returns using panel data for pharmaceutical companies listed on IDX [4]. The authors focus on several fundamentals including the current ratio, return on equity, net profit margin, debt-to-equity ratio, and earnings per share. The paper uses data from a period between 2013-2017, utilizes panel data, and focuses on companies from a single sector, which makes it relevant to this research. Anjani and Syarif [4] find relationships between certain fundamentals and stock returns, yet they fail to explain the theoretical logic behind these relationships producing unreliable results, which cannot be used for further research.

CHAPTER 2. METHODS AND MATERIALS

2.1. Methodology

The study uses panel data to analyze the relationship between tech firms' fundamentals and their stock returns. The companies are selected from the NASDAQ 100 Technology Sector Index. The explanatory variables utilized are book-to-market ratio, price-to-earnings ratio, return on assets, leverage ratio, current ratio, and earnings per share. The dependent variable is a one-quarter ahead stock return.

According to Baltagi [7], in comparison to time series or cross-sectional data used separately, panel data presents more informative results of better quality, has less collinearity between variables, and offers more degrees of freedom. The panel data approach gained more popularity in the research dedicated to fundamental analysis after the 1990s, however, it is still often combined with the portfolio strategy.

This study is limited to stock market data from 31 companies in the tech sector. The panel data can be defined as long and fixed as the entities remain constant. The panel data is unbalanced as data is not available for all entities throughout the whole period of observation. The reason is the relative newness of the sector and the high growth rates that are common for tech companies. Even among the top 30 companies in the index, some have been public for just a few years. After the data is filtered (the observations for which data was missing were removed from the sample) the total number of observations is 1019.

For the analysis of the panel data, the choice is usually made between one of the three models: Pooled OLS, Fixed Effect, or Random Effect models. The selection of a model depends on the presence and nature of the individual-specific effects and can be determined by theoretical reasoning in combination with corresponding tests. The approaches to panel

data analysis differ, however, the key difference is usually just the order of steps. The approach utilized in this paper is summarized in Figure 2.1.

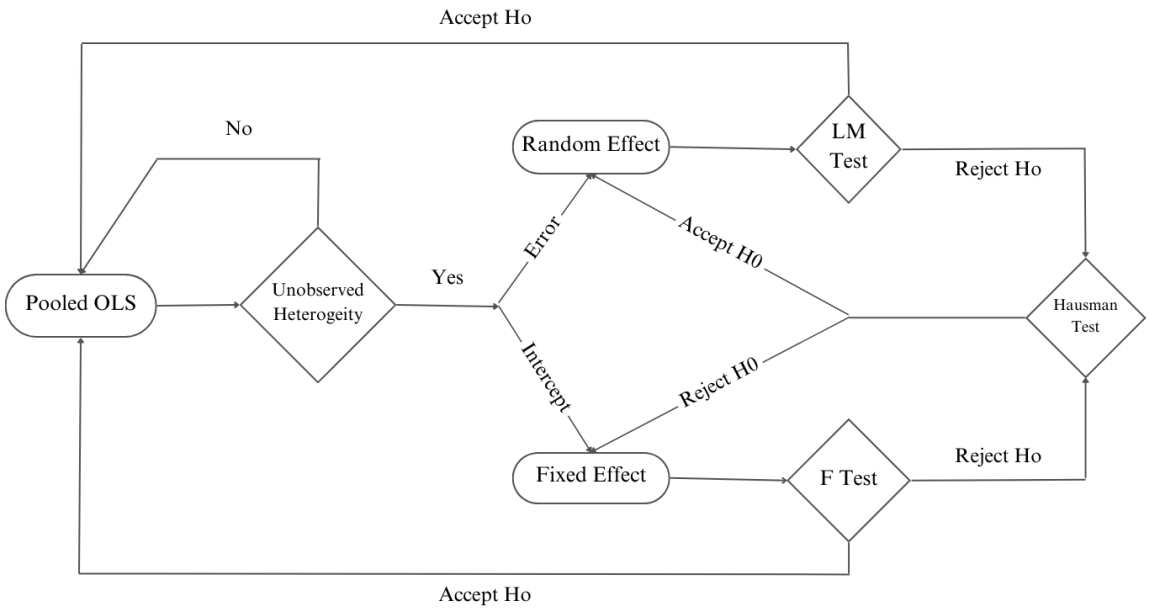

Figure 2.1. Methodological approach to panel data analysis

Source: created by the author based on Park (2011)

If time-specific or cross-sectional effects do not exist, then a simple Pooled OLS can be used. For the model to be utilized the five basic assumptions must hold. (1) Linearity - the relationship between dependent and independent variables must be linear, (2) Exogeneity - error terms must not be correlated with the explanatory variables and their expected value must be zero, (3.1) Homoscedasticity - variance of the error terms must be constant, (3.2) No autocorrelation - error terms must have no autocorrelation, (4) Multivariate normality - explanatory variables must not be stochastic, and (5) Non-collinearity - explanatory variables must not have a linear relationship [26: 11-19; 28: 41-42].

The existence of heterogeneity because of individual effects will affect assumptions 2 and 3 and will not allow Pooled OLS to produce reliable results. For example, if the values vary across individuals and error terms don't have the same distribution then the assumption of homoscedasticity (3.1) will be violated. The violation of any of these assumptions

suggests that instead of Pooled OLS a fixed or random effect model should be used. The approach of this paper is to start with a simple Pooled OLS and test if assumptions 2, 3.1, and 3.2 hold for the model.

If Pooled OLS violates any of the assumptions a choice between employing Fixed or Random Effect models is made. According to Kennedy (28: 282-286), the key difference between the models is not whether a dummy variable becomes a part of the intercept (fixed effect) or a part of the error term (random effect) but rather whether the individual effect is correlated with regressors. A Fixed Effect model is applied when individual effects are assumed invariant, while a Random Effect model assumes individual heterogeneity to be random. An important assumption of the Random Effect model is that individual effects are not correlated with the regressors.

The models' theoretical equations look like this (Eq. 2.1, 2.2):

Fixed Effect: $Y_{it} = (\alpha + \mu_i) + \beta X_{it} + \nu_{it}$, (2.1)

Random Effect: $Y_{it} = \alpha + \beta X_{it} + (\nu_{it} + \mu_i)$, (2.2)

In this formula μi is a fixed or random effect specific to individual or period that is not included in the regression [37]. From the equations, it is visible how the unobserved heterogeneity becomes is recorded in the intercept in the Fixed Effect model and error term in the Random Effect model.

Park [37] illustrates the difference between Fixed and Random Effect models with a simple example. His example is the regression of companies' production on their R&D investment. Fixed effect in this case can be interpreted as the initial production of each company with zero R&D. A Random Effect Model can be viewed as consistency of production, when one firm's production has a higher variation than another.

The F-test is often used to test if a Fixed Effect model can yield significantly better results than Pooled OLS while the LM test is used to test for the random effects. If the null hypotheses for either of the two are not rejected, then Pooled OLS is advised as long as it

passes the Chow test for poolability. A Hausman test is used to compare Fixed and Random Effect Models. Its null hypothesis is that individual effects are not correlated with the regressors. If it is not rejected, the Random Effects model is used.

The approach of this research is to start with the simplest model and then use more complicated models if needed. Despite the manual selection of firms in many ways similar (industry, size) a presence of an individual effect is still very likely as these firms have many unique characteristics that likely impact their returns, for example, Intel went public in 1971 while Meta was listed only in 2012. It is assumed that time-specific effects should not be sources of unobserved heterogeneity because of the relatively short and homogenous period of observation. A one-way model was applied first.

2.2. Data

The stock price data and the firm's fundamentals are retrieved from the GFD Finaeon database. The data for 31 companies traded on the NASDAQ-100 Technology Sector Index (NDXT) is used for the research. The complete list of companies that were used in the research can be found in Appendix A. The data is quarterly as it is retrieved from the company's quarterly (form 10-Q) and annual (form 10-K) reports. The data covers a period between the first quarter of 2012 and the last quarter of 2022. The extension of the sample is one of the possible directions for the results' quality improvement, however, with the panel data being used and the quarterly frequency of recordings the sample selected should be able to generate results of sufficient quality.

2.3. Measures

Return

As companies' fundamentals are retrieved from their quarterly and annual reports which are usually published with a delay a time gap should exist between the publishing

time of fundamentals and the time when the corresponding stock return is recorded to make sure that the effect of the factors is recorded. The other reason for using a lag is the theory of underreaction described in the literature review. Fama and French used the 6-months gap between the date on which price was used to calculate return and fiscal yearend [18]. As quarterly data is used, the return linked to fundamentals is recorded for the next quarter after the fundamentals are published. In the academic literature, different approaches to recording returns can be found. Some authors record returns using the prices for the first and last days of the recorded period. In contrast, others note that this method is receptive to unexpected price fluctuations and can generate results that are much noisier suggesting that using average return over the period is better. After some experiments, it was decided to use an average quarterly return as it was able to yield significantly better results by limiting noisy fluctuations of price. The formulas used to calculate returns and all the explanatory variables are presented in Table 2.1.

Table 2.1. Formulas used to calculate the variables

Variable	**Formula**
Stock Return (next quarter)	$R_{(t+1)} = \ln \frac{Pt+1}{Pt}$
Price-to-Earnings ratio	$\text{P/E Ratio} = \frac{Market\ value\ per\ share}{Earnings\ per\ share}$
Book-to-Market ratio	$\text{Book-to-Market} = \frac{Common\ Shareholders'\ Equity}{Market\ Capitalization}$
Return on Assets	$\text{Return on Assets} = \frac{Net\ Income}{Total\ Assets}$
Leverage Ratio	$\text{Leverage Ratio} = \frac{Total\ Liabilities}{Total\ Assets}$
Earnings per Share	$\text{EPS} = \frac{Net\ Income}{Total\ Shares\ Outstanding}$
Current Ratio	$\text{Current Ratio} = \frac{Current\ Assets}{Current\ Liabilities}$

Source: created by the author

Fundamentals

The choice of the independent variables was an essential part of the study. It was guided by the findings of other papers dedicated to examining the relationship between fundamental analysis and stock returns. It should be noted that the choice of ratios was to some extent limited by the access to data and the ability to process it, however, this doesn't have a significant impact on the quality of the model and the results.

The scope of the research, the hypotheses, and the questions central to the study shaped the selection of ratios. Using data about the performance of five American technological companies with relatively similar market capitalization made the use of some of the often-examined independent variables redundant. On the other hand, most of the variables included in the model have been often used by academics throughout the last few decades of research, however, never in this context.

The explanatory variables are used with a natural logarithm to normalize distribution as some measures (e.g. PE ratio) were extremely skewed. The return is calculated as a natural logarithm.

Finally, the general empirical equation is the following (Eq. 2.3):

$$R_{t+1} = \beta_0 + \beta_1 (\ln(pe_{it})) + \beta_2 (\ln(book\_to\_market_{it})) + \beta_3 (\ln(eps_{it})) + \beta_4 (\ln(roa_{it})) + \beta_5 (\ln(current_{it})) + \beta_6 (\ln(leverage_{it})) + e\ \mu_t, \quad (2.3)$$

Fundamentals: Price-to-Earnings ratio (P/E)

The Price-to-Earnings ratio is calculated as the relation of a firm's current stock price to its earnings per share (EPS). This ratio is also known as the earnings multiple or price multiple and is one of the most widely used ratios to analyze and compare a company's fundamentals. This ratio provides information on the relative value of a company, and it can be used for the analysis across companies or to compare the historical relative valuation of a single firm.

This ratio provides information on whether a company is likely to be overpriced or underpriced by telling how much investors are currently ready to pay for 1 unit of the company's profits. A comparatively high P/E could be an indicator of a firm being overpriced or investors expecting high future profits.

It is best practice to compare the P/E ratios of companies within the same industry as a mean ratio usually varies across industries. This makes the application of the Price-to-Earnings ratio for this research paper especially applicable because companies of the same industry are analyzed.

There are two common approaches to calculating the P/E ratio: trailing and forward. The trailing P/E ratio most commonly uses EPS data for the last 4 quarters, while forward P/E is based on estimations of future earnings [23]. The average P/E for S&P 500 has changed a lot over time, from as low as 5.31 in 1917 to 123.73 in 2009 right before the financial crisis.

Fundamentals: Book-to-Market Ratio

The book-to-market ratio is calculated by dividing the common shareholder's equity by a company's market capitalization. Shareholders' equity can be calculated as the difference between a firm's assets and liabilities. Extracting total shareholders' equity from the balance sheet is one of the possible ways to retrieve a company's book value.

Like the P/E ratio, Book-to-Market provides information on whether a company is likely to be undervalued or overvalued. A ratio above 1 would mean that the book value of the company is higher than what it's traded for on the market, while a ratio below 1 means the company is traded for more than its book value. Stocks with a ratio bigger than 1 are often called "value stocks" and they are preferred by investors, while stocks with a ratio below 1 are more likely to be overvalued. Stocks with low book-to-market ratios are called "growth stocks" and they tend to yield significant negative excess returns [14]. This is often referred to as a value effective and it is well recorded in financial academic papers. In this paper a reverse relationship was observed. Possible reasons will be discussed in the last

section. Fama and French [18] and Lakonishok, Shleifer, and Vishny [30] recorded that the relationship between stock returns and book-to-market ratio exists, however, the source of this dependency is still unclear and was attributed either to the unobserved risk or to the mispricing of the stocks.

Fundamentals: Return on Assets

Return on assets provides information on the profitability of a company concerning its assets and is calculated by dividing a firm's net income by its total assets. This ratio is a measure of how efficiently a company manages its balance sheet with a higher ratio signalizing a higher efficiency or higher yield on assets.

Fundamentals: Leverage Ratio

The leverage ratio measures what percentage of a firm's capital comes from borrowing compared to issuing equity. There are different measures of leverage including debt-to-equity and debt-to-market capitalization, but this research uses the ratio of total liabilities to total assets as a measure of leverage. A high leverage ratio means that a large part of a firm's assets is financed by debt which increases the risk associated with the firm's performance and ability to pay the debt out. On the other hand, a very low leverage ratio may also raise concerns by being a possible indicator of a firm's inability to qualify for financing.

Fundamentals: Earnings per Share

To calculate EPS firm's net income has to be divided by the total number of its shares outstanding. Some adjustments can be made to the formula to make calculations more precise like subtracting preferred dividends from net income value or subtracting options convertible debt or warrants from the number of shares outstanding. EPS is also one of the leading fundament indicators of a firm's performance and it is used to calculate the P/E ratio. EPS shouldn't be used as a meaningful instrument for comparison between different

companies as the number of common stock outstanding differs across companies and P/E would fit that purpose better. However, EPS can be used for comparing one firm's performance over time.

Fundamentals: Current Ratio

The current ratio is a measure of a company's liquidity, and it is calculated by dividing a company's current assets by its current liabilities. It measures a firm's ability to pay out its short-term debt and the current ratio of different companies should be compared within the same industry. If the current ratio of a company is close to the average ratio in the industry, then it is liquid enough and able to payout its debt. A low current ratio is usually a negative signal to investors, and it raises concerns about a company's ability to pay out debt, while a particularly high current ratio may be an indicator of inefficient management of assets.

CHAPTER 3. RESULTS AND FINDINGS

3.1. Estimating regression

Based on the results of the conducted testing the Fixed Effect model was selected as the best-fitting model to address the research question. However, before the results of the Fixed Effect model are analyzed in greater detail the decision-making process will be briefly described in this section. First, the Pooled OLS regression was estimated, and its output can be seen in Figure 3.1.

When a Pooled OLS regression was applied, four out of six independent variables were significant at a 0.05 significance level, while the P/E ratio and Book-to-Market ratio were not significant. The R^2 for this regression is 0.042 indicating that the variation of independent variables explains little of the dependent variable's variation. The Model's F-statistic is 7.315 and the p-value is close to zero leading us to conclude that the model's coefficient estimates are jointly significant at a $p < .001$.

After running the tests to determine the goodness of fit of the Pooled OLS model it could be concluded that several assumptions were violated. The Q-Q plot was constructed to analyze if the residual errors were normally distributed. The graph in Figure 3.2 indicates that residuals are not normally distributed which is supported by the Jarque-Bera test (Figure 3.1) test indicating that residuals are not normally distributed at $p < .001$.

With the lack of normal distribution of the residual error terms Pooled OLS does not have a critical impact on the model's performance. This, however, can cause problems when building confidence intervals.

Dep. Variable:	next_r			
No. Observations:	1019			
Variables	**Coef.**	**Std. errs.**	**t**	**P > | t |**
Intercept	0.2520	0.053	4.733	0.000
Log_pe	0.0202	0.012	1.727	0.084
Log_book_to_market	0.0128	0.025	0.511	0.610
Log_eps	-0.0565	0.021	-2.721	0.007
Log_roa	0.1019	0.029	3.455	0.001
Log_current	0.0879	0.035	2.520	0.012
Log_leverage	-0.2109	0.043	-4.952	0.000
R-Squared:	0.042		F-statistic:	7.315
Adj. R-Squared:	0.036		Prob.(F-stat)	1.14e-07

Figure 3.1. Results of the Pooled OLS model

Source: estimated by the author

To test for heteroscedasticity residuals were first graphed with the independent variables and no obvious pattern was spotted. However, the LM test's p-value for the White test was less than 0.001 indicating a rejection of the Null hypothesis that residuals are homoscedastic. The heteroskedasticity of the residuals is a violation of one of the five assumptions of a linear model. According to that Pooled OLS isn't BLUE and either a Fixed or Random Effect model should be used.

An almost perfect correlation was also spotted between the dependent variable and residuals (Figure 3.3). The value 0.98 of Pearson's correlation coefficient indicates a 98% correlation between a dependent variable and residuals, meaning that most of the return's variation remains unexplained by the model and it is caused by some other unobserved factors.

The Auto-Correlation Function (Figure 3.4) indicates that residuals are strongly positively autocorrelated at a large number of lags. The Durbin-Watson test result of 0.42 also indicates a strong positive autocorrelation present in the model.

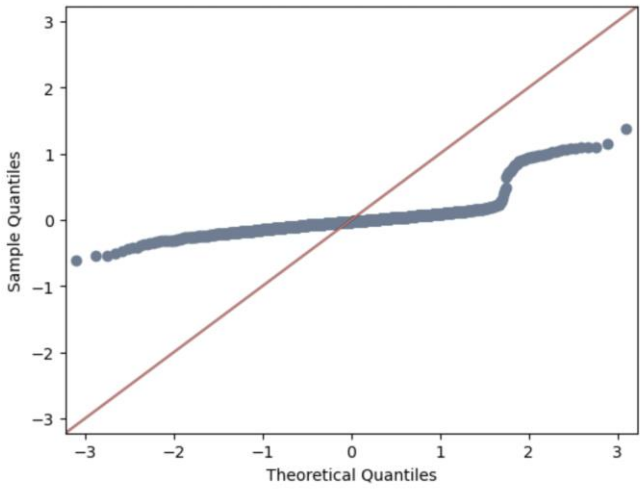

Figure 3.2. Q-Q plot of the residual errors

Source: estimated by the author

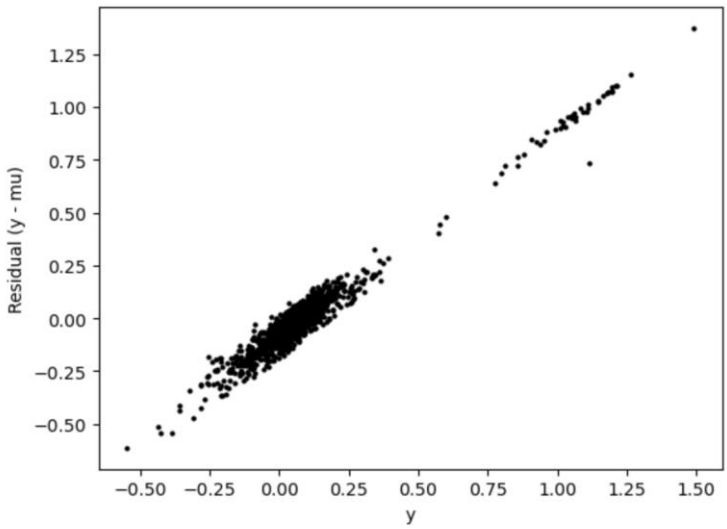

Figure 3.3. Raw residuals of Pooled OLS versus Y

Source: estimated by the author

Both the no autocorrelation and homoscedasticity assumptions for the Pooled OLS model have been violated which means that the model is not BLUE, and a different model

should be used. In addition, the model has a very low explanatory power with R^2 at 4% and almost a perfect correlation between residuals and dependent variable.

Since Pooled OLS cannot be used Fixed and Random Effect models were estimated. The results of the Fixed Effect model can be seen in Figure 3.4 and the Random Effect model's results are in Figure 3.5.

The one-way Fixed Effect model with individual specific effects was used and it was able to yield significantly better results than the Pooled OLS. R^2 for this model is 0.76 meaning that the model explains 76% of returns variation. The F-statistic also increased significantly to 92.73 with a p-value close to zero. Book-to-market ratio, earnings per share, return on assets, current ratio, and leverage are significant at a 0.05 significance interval, while the P/E ratio remained insignificant.

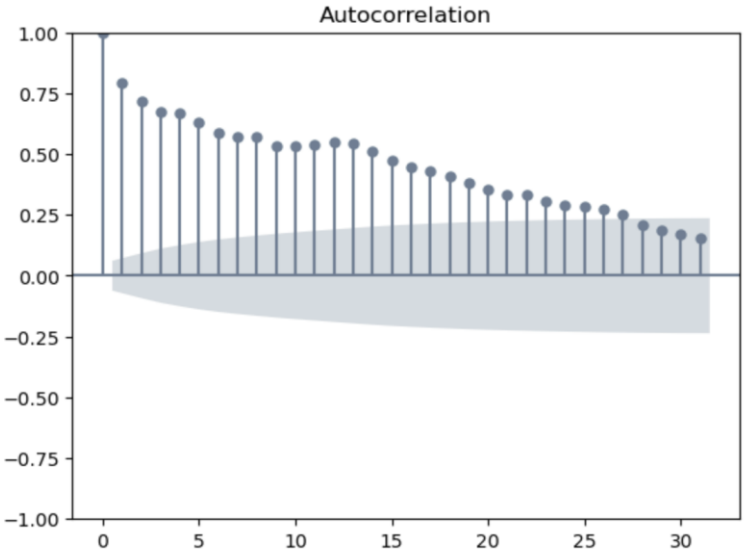

Figure 3.4. The auto-correlation function

Source: estimated by the author

A restricted F-test was then used to determine whether the fixed effects are present and if the Fixed Effect model should be used instead of the pooled OLS. The F-test tested the null hypothesis which states that country-specific effects are jointly zero. The test is run

to compare the restricted model, in this case, Pooled OLS, to the unrestricted model, which is a Fixed Effect. The formula for the F-statistic is the following (Eq. 3.1):

$$F - statistic = \frac{\frac{(RSS(restricted\ model) - RSS(unrestricted\ model))}{(k2 - k1)}}{\frac{RSS(unrestricted\ model)}{(N-k2)}}, (3.1)$$

F-statistic for the FE model is 106.45, that is much higher than the F test critical value at the alpha of 0.05 which equals to 1.49 indicating that individual specific effects are present and Fixed Effect model is a much better fit. The redundant Fixed Effect test also indicates the presence of fixed effects significant at a $p < .001$.

The output of the Random Effects model is depicted in Figure 3.5. The same five variables are significant at 0.05 level, while the P/E ratio remains insignificant. The f-statistic is 13.2 with the p-value close to zero, while R-squared is 0.073, a bit higher than the Pooled OLS, however, much lower than the Fixed Effect. The LM test indicated a presence of firm-specific Random Effects at a $p < .001$.

Since both Fixed and Random Effects are present a common approach would be to run a Hausman test to determine which model would be a better fit. The null hypothesis of the test is that individual effects are uncorrelated with any regressor in the model. If the null hypothesis is not rejected Least-squares Dummy Variable (LSDV) and Generalized Least Squares model can be used, but LSDV will not be as efficient.

The Hausman test has a p-value of 0.72 indicating that the null hypothesis shouldn't be rejected, and the random effect model should be used. However, estimates of the goodness of fit demonstrate that the fixed effect model can explain a lot more of the return's variation (Table 3.1).

Dep. Variable:	next_r			
No. Observations:	1019			
Variables	**Coef.**	**Std. errs.**	**t**	**P > | t |**
Intercept	-0.0121	0.054	-0.225	0.822
Log_pe	0.0121	0.007	1.771	0.077
Log_book_to_market	-0.1214	0.022	-5.624	0.000
Log_eps	-0.1352	0.020	-6.613	0.000
Log_roa	0.1218	0.023	5.379	0.000
Log_current	0.0647	0.029	2.214	0.027
Log_leverage	-0.1607	0.037	-4.371	0.000
R-Squared:	0.762		F-statistic:	92.73
Adj. R-Squared:	0.754		Prob.(F-stat)	1.41e-279

Figure 3.4. Results of Fixed Effect model

Source: estimated by the author

Dep. Variable:	next_r			
No. Observations:	1019			
Variables	**Coef.**	**Std. errs.**	**t**	**P > | t |**
Intercept	0.1820	0.055	3.327	0.001
Log_pe	0.0128	0.007	1.874	0.061
Log_book_to_market	-0.1140	0.021	-5.304	0.000
Log_eps	-0.1306	0.020	-6.482	0.000
Log_roa	0.1184	0.022	5.275	0.000
Log_current	0.0642	0.029	2.210	0.027
Log_leverage	-0.1616	0.036	-4.434	0.000
R-Squared:	0.073		F-statistic:	13.20
Adj. R-Squared:	0.067		Prob.(F-stat)	1.98e-14

Figure 3.5. Results of Random Effect model

Source: estimated by the author

Table 3.1. A comparison of goodness-of-fit measures of the models.

	Pooled OLS	Fixed Effects	Random Effects
Adjusted R-squared	0.036	0.754	0.067
Log-Likelihood	59.100	769.12	754.30
AIC	-104.2	-1468	-1495

Source: estimated by the author

Adjusted R-squared is significantly improved when the Fixed Effect model is used. Log-likelihood and AIC also see some improvement when the Fixed Effect model is used.

The Fixed Effect model is generally more commonly used as it is usually much more convincing than RE for policy analysis using aggregated data [46]. The assumption that unobserved heterogeneity is uncorrelated with the regressors is hard to hold and the selected companies aren't likely to be a random sample from a large population.

Although using Random Effects would allow making some predictions about the general population, using Fixed Effects is likely to produce more robust results. Fixed Effect models are usually able to provide more consistent estimates than Random Effect models as it is usually difficult to be certain that the key assumption for Random Effect is not violated. Although the Fixed Effect model may not be as efficient in this case, consistency is prioritized and selected over efficiency.

One reason for the low R-squared value of the Random Effect model in comparison to the Fixed Effect can be attributed to certain characteristics of the panel data used. First of all, panel data is unbalanced, while 40 observations are available for some companies, others have less than 10. Fixed individual effects are likely to be highly significant as well as companies in the panel data differ significantly by their maturity, capitalization, and product stream.

The Fixed Effect model doesn't cancel out but significantly limits the omitted variable bias by accounting for the unobserved heterogeneity. This improves the goodness-of-fit of the model, however, wipes out any time-invariant factors. The Fixed Effect model has resolved the issue of autocorrelation as can be observed when we compare Figure 3.6 to Figure 3.4. Durbin-Watson coefficient has also improved to 1.481, however, at this value it is inconclusive.

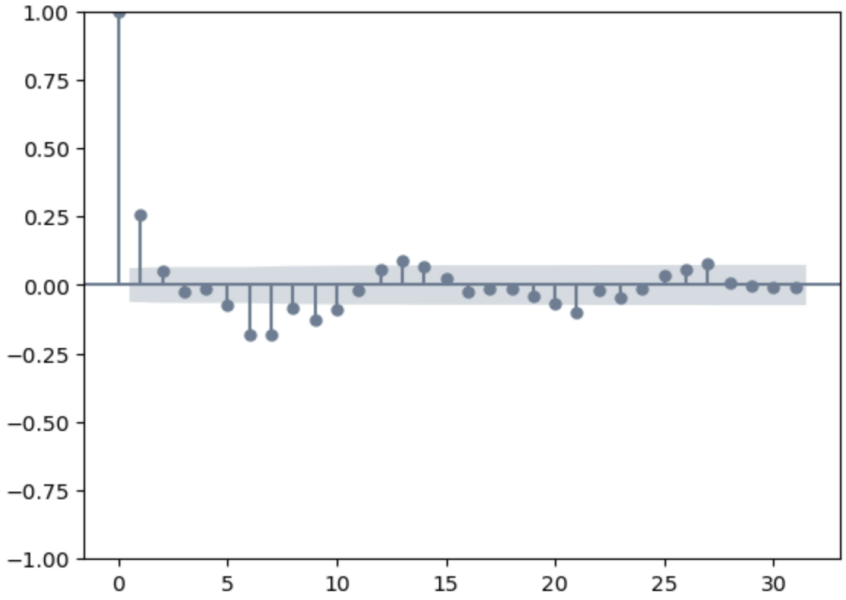

Figure 3.6. Auto-correlation in Fixed Effects model

Source: estimated by the author

From the correlation matrix in Figure 3.7 we can also rule out an issue of multicollinearity.

	LOG_BOOK_	LOG_CURR	LOG_EPS	LOG_LEVER	LOG_PE	LOG_ROA
LOG_B	1.000000	0.171773	-0.214286	0.080097	-0.172607	-0.118740
LOG_C	0.171773	1.000000	-0.014908	0.559747	-0.002466	0.129628
LOG_E	-0.214286	-0.014908	1.000000	-0.076981	-0.383898	0.683370
LOG_L	0.080097	0.559747	-0.076981	1.000000	0.001737	0.006716
LOG_PE	-0.172607	-0.002466	-0.383898	0.001737	1.000000	-0.233337
LOG_R	-0.118740	0.129628	0.683370	0.006716	-0.233337	1.000000

Figure 3.7. Correlation matrix of explanatory variables

Source: estimated by the author

Finally, the Fixed Effect model with one-way entity-specific effects is selected as the best fitting for the purposes of this study. The results yielded by the model and their plausibility is analyzed in the next section of the paper.

3.2. Discussion and analysis

Out of six explanatory variables used to explain the variation of return current ratio, leverage, earnings per share, and return on assets are significant at 0.01 significance level and book-to-market ratio is significant at 0.05 significance level. The P/E ratio is insignificant at either of the significance levels. Overall, the results of the model align with the expectations about the nature of the relationship and with the previous findings documented in relevant papers. However, some unexpected results require some explanation. In this section of the paper, the relationships are briefly covered and linked to possible theoretical explanations.

Price-to-Earnings is not significant and doesn't explain the variation of return of selected tech companies for the period from 2012 to 2022. The relationship between E/P (reverse of P/E) was well-documented in the works of the late 20th century. Among the studies covered in the literature review that documented the relationship between returns and E/P are those of Basu [11] and Fama and French [18]. Both papers found that on average higher dividend yield (E/P) was associated with higher average returns. Fama and French [18], however, did not argue for the E/P explanatory power but rather suggested that it comes from the correlation with the book-to-market ratio.

The book-to-market ratio has a coefficient of -0.1214 indicating that a negative relationship exists between this explanatory variable and the average return for the next period. This also goes against the major works that have been used as a foundation for this study. Fama and French [18] recorded a strong positive relationship between book-to-market ratio and returns. They provided two theories explaining the nature of the relationship: 1)

book-to-market catches additional risk factors that are not accounted for in CAPM; 2) it may capture market overreaction to relative prospects of firms which is corrected with time [16]. Chen and Zhang [15] come to similar conclusions about the nature of the relationship while Dichev's [17] findings do not align with the theory. In our case, a negative relationship is observed between the book-to-market ratio and stock returns, meaning that a lower book-to-market ratio is associated with higher future stock returns. This finding doesn't align with the theory that firms with high BE/ME are riskier and thus earn a higher risk premium. It can, however, be assumed that a low book-to-market is an indicator of higher future earnings, however, the market underreacts to the information and adjusts the price with a time lag as suggested by Abarbanell and Bushee [2].

The coefficient next to Earnings per Share is -0.1352 also indicating a negative relationship. One possible explanation that can be found in the works of Barth et al. in 2014 and Habib and Faid may be that earnings growth and higher reported earnings can be interpreted by investors as an accounting manipulation when they can assess whether it is caused increased revenue or reduced expenses [3; 27].

Return on assets and current ratio are both positively related to next period average returns. It is unlikely that either of the measures can be a proxy for unrecorded risk. It can, however, potentially be explained by underreaction to the positive fundamental information. A higher return on assets is a signal of a likely increase in productivity and more effective use of resources while the increased current ratio is a signal of increased liquidity and thus improved financial stability (with some limitations).

The leverage is negatively related to the next period's average returns with a coefficient of -0.1607. Bhandari [13] reported a positive relationship between leverage and return and Fama and French [18] have linked leverage to book-to-market ratio also inclining towards the same interpretation. This study uses a different measure of leverage than the two mentioned studies, the leverage in this case is calculated as total assets divided by total liabilities. Higher leverage is associated with a higher risk and thus should result in higher returns, but this line of reasoning is not supported by the regression results. Penman et al.

[38] produced findings that align with those of this research as they found a negative relationship between leverage and returns. The relationship passed multiple tests and was held after other factors were included in the regression. The authors were surprised by the finding and called it another anomaly when “good” factors yield higher returns and “bad” yield lower returns.

CONCLUSION

This study aimed to explain the theoretical relationship between fundamental factors and the return on holding the firm's shares as well as empirical estimation of such relationships. The theoretical reasoning behind the research is closely linked to the work of Abarbanell and Bushee [2] who proposed a theory of delayed price adjustment to new pieces of information. By assuming that markets may underreact to fundamental information in the short term this work challenges the efficient market hypothesis, however, doesn't find enough evidence to reject it. Six fundamental measures: P/E ratio, book-to-market ratio, return on assets, earnings per share, current ratio, and leverage were used to explain one-quarter-ahead average stock returns were used. The study focused on a single sector, selecting 31 companies from the NASDAQ 100 Technology Sector Index. The data used covered a period between 2012 and 2022 and was recorded at quarterly intervals. After all the necessary tests were conducted the Fixed Effects, model was selected. According to the results that it yielded five out of the six explanatory variables were found significant at a 0.05 significance level. Book-to-market ratio, current ratio, earnings per share, return on assets, and leverage are significant while P/E was found to be insignificant in explaining average returns with a one-period lag.

Most findings of the study align with those of some of the well-acknowledged and widely cited papers, however, some results are debatable and require further analysis for better interpretation. The theory of underreaction and delayed incorporation of fundamental information proposed by Abarbanell and Bushee [2] heavily influenced the line of interpretation and was used as a theoretical foundation to argue for the possible predictive power of the fundamental indicators. The findings, however, to a large extent didn't align with the works of Fama and French published in the 1990s, who mostly argued for the efficiency of the markets.

The underreaction theory challenges the efficient market hypothesis as it is based on the idea that markets do not incorporate all the available information into the price. The recorded effect of leverage also raises some questions as to what extent markets are efficient with little possibility that this factor may be associated with extra risk.

The insignificance of the P/E ratio in explaining future returns and the opposite of the expected nature of the relationship between book-to-market and returns remain without robust explanation and suggest that further and more detailed research on the topic is necessary to draw plausible conclusions.

Nevertheless, despite the limitations the paper indicates interesting issues and relationships which could lead to the construction of a model that could predict future returns in the short term. The model has limitations and multiple areas for possible future improvement. First, the findings for the tech sector should be compared with those for the market-wide selection of companies over the same time horizon. It should provide more information as to whether the P/E effect disappears overall or is just not existent in the selected sector. Secondly, the sample should be extended to include a larger number of companies and a longer period. Out-of-the-sample testing would also improve the robustness of the results. Finally, the list of explanatory variables can be extended and multiple lags for average return can be compared to see if the underreaction hypothesis holds and if its effect disappears after one quarter.

APPENDIXES

Appendix A. Tech companies used in the research

Ticker	**Company name**	**Year of listing**	**Segment**	**Market cap (10/05), billion USD**
AAPL	Apple Inc.	1980	Consumer Electronics	2714
ADI	Analog Devices, Inc.	1969	Semiconductors	91.06
AMAT	Applied Materials, Inc.	1972	Semiconductors	96.72
AMD	Advanced Micro Devices, Inc.	1972	Semiconductors; Artificial intelligence; Consumer electronics	156.30
INTC	Intel Corporation	1971	Semiconductors; Artificial intelligence; Computer hardware	123.15
INTU	Intuit Inc.	1993	Enterprise Software;	119.98
MCHP	Microchip Technology Inc	1993	Semiconductors	40.31
MSFT	Microsoft Corp	1986	Information technology	2303
SNPS	Synopsys Inc	1992	Integrated circuit; Self-driving cars; Software as a service; Software Testing	55.68

TXN	Texas Instruments Inc	1953	Semiconductors; Integrated circuit; Embedded processors	146.52
ADBE	Adobe Inc	1986	Software	158.64
ADSK	Autodesk Inc	1985	Software	42.01
ANSS	ANSYS, Inc.	1996	Software	25.42
ASML	ASML Holding NV	1995	Semiconductors	262.94
CDNS	Cadence Design Systems Inc	1987	Software; Integrated circuit;	55.52
KLAC	KLA Corp	1980	Semiconductors	52.55
LRCX	Lam Research Corporation	1984	Semiconductors	70.32
MU	Micron Technology Inc	1984	Semiconductors	65.89
NVDA	NVIDIA Corporation	1999	Computer hardware; Computer software; Cloud computing; Semiconductors; Artificial intelligence;	711.40

QCOM	Qualcomm Inc	1991	Telecoms equipments; Semiconductors	118.04
AVGO	Broadcom Inc	1998	Semiconductors; Computer software;	259.37
CTSH	Cognizant Technology Solutions Corp	1998	Information technology; Consulting; Outsourcing;	31.51
FTNT	Fortinet Inc	2009	Cloud Security; Cybersecurity; Network Security;	52.55
GOOGL	Alphabet Inc	2004	Artificial intelligence; Advertising; Cloud computing; Computer software; Computer hardware; Internet;	1.42
META	Meta Platforms Inc	2012	Social media; Social network advertising; Consumer electronics; Virtual reality;	596.85
MRVL	Marvell Technology Inc	2000	Semiconductors	34.64
TEAM	Atlassian Corp	2015	Software	34.97
WDAY	Workday Inc	2012	Cloud computing; Enterprise software;	46.16
PDD	PDD Holdings Inc - ADR	2018	Internet; Agriculture; E-Commerce;	80.19

ZM	Zoom Video Communications Inc	2019	Software	18.86

Source: created by the author

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