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Biotech - the End of Big Pharma?

Given the risks of investments in biotechnology and pharmaceutical stocks, have the returns exceeded what would be predicted by financial asset pricing models?

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This thesis was written as part of our Master's degree in Economics and Business Administration at the Norwegian School of Economics (NHH), where we have specialized in Financial Economics, and Business Analysis and Performance Management.

The objective of this thesis has been to contribute to existing literature with a relevant and quantitative analysis. As two students with a particular interest in the biotechnology and pharmaceutical sector, we were inspired to study the returns and risk factors of stocks in these sectors.

The process of completing this thesis has been challenging, yet highly intriguing and educational. We have acquired valuable knowledge of biotech and pharma stocks. Furthermore, we have obtained quantitative skills by applying financial theory in econometric analysis. We have also improved our skills in RStudio, Microsoft Excel and LaTex.

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Abstract

The objective of this thesis is to investigate whether biotech and pharma stocks have exceeded the returns of what would be predicted by financial asset pricing models. More specifically, we examine whether the stocks in these sectors have delivered positive abnormal returns. We study value-weighted biotech portfolios and pharma portfolios with return data from January 2010 to June 2022. We limit the analysis to stocks in developed countries.

We apply the Fama-French five-factor model, in which the dependent variable is the excess return over the risk-free rate. The estimated alphas determine the existence of abnormal returns. We study different regions, time periods and comparable sector indices in our main analysis. We also conduct a robustness analysis with results from other multi-factor models, as well as portfolios with annually rebalancing and equally-weighting.

We find significantly positive alphas for the value-weighted biotech portfolio in Europe and the equally-weighted biotech portfolio in developed countries, i.e., these portfolios deliver positive abnormal returns. We discuss the potential of R&D as a systematic risk factor that can explain the abnormal return. We do not find any significant abnormal returns for the pharma portfolios. Moreover, we find that both biotech and pharma stocks are positively exposed to the market factor and negatively exposed to the value factor. Additionally, the biotech portfolio is positively exposed to the size factor and negatively exposed to the profitability factor. The pharma portfolio is positively exposed to the investment factor.

Keywords: Biotech stocks, Pharma stocks, Abnormal returns, Fama-French factor models

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The days of big pharma are over,

and the era of big biotech has only just begun.

JOSH NATHAN KAZIS

1 Introduction

Internal product innovation, in-licensing[1] and acquisitions activities have long served as the recipe for success in the pharmaceutical (hereafter pharma) industry. Nonetheless, the flow of innovation has recently stagnated as a wave of biotechnology (hereafter biotech) firms has arisen. Biotech firms, which at first were met by chuckles from big pharmas some forty years ago, have now come to revolutionize the future of health care (Burns, 2020). The number of firms competing for the profit pool in biotech has more than tripled during the last decade. Accordingly, the total market capitalization of North American biotech firms has accelerated from 63 billion dollars in 2010 to 800 billion dollars as of June 2022. Pharma firms have responded with biotech-targeted restructurings and acquisitions, which has likely had a positive influence on the valuation and market prices of biotech stocks (Hoffman, 2022; Bayer AG, 2022; Ipsen SA, 2022).

To put it simply, the investor appetite seems to have surged from pharma to biotech firms. There are multiple explanations for why investors believe there is almost what seems like an unlimited potential in the biotech sector. The potential of therapeutic proteins, antibodies and peptides are intriguing. In addition, the idea of personalized health care with DNA and RNA molecules is revolutionary. Nonetheless, investors also seem to value the steady nature of the pharma sector. The sector is characterized by steady cash flows given the almost inelastic demand (Burns, 2020).

Investors can deliberately construct portfolios of biotech stocks and portfolios of pharma stocks if they believe in the potential of these sectors. The portfolios will have a considerable amount of unsystematic risk given their targeted sector exposure. Some argue that the unsystematic risks of biotech and pharma investments can provide positive abnormal returns. The sectors are exposed to government risks, huge R&D spending, long commercialization periods, and low hit ratios in R&D projects (Dong and Guo, 2013; Koijen et al., 2016). Hence, investors in biotech and pharma stocks should earn a premium. Furthermore, some argue that pharma stocks can deliver positive abnormal returns over time due to their steady cash flows. Others argue that biotech stocks have additional

[1]In-licensing occurs when the owner of a technology or product, the licensor, grants a third party, the licensee, a share of the rights to the product or technology. Thus, research and development (R&D) costs, and regulatory and financial risks are shared between the parties (Burns, 2020).

potential due to the possibility of detecting entirely new technologies.

Using data on publicly traded stocks, we examine the returns of 1,076 biotech and pharma stocks in developed countries. The objective is to answer whether the returns of biotech and pharma stocks have exceeded the expectations of asset pricing models. We estimate alphas to determine the existence of abnormal returns. We apply the Fama-French five-factor model in our main analysis, in which the dependent variable is the excess return over the risk-free rate. Supplementary analyses of continents, various time periods and sector indices will ensure a thorough examination. In addition, we include a robustness analysis with different multi-factor models, annually rebalancing and equally-weighted portfolios. In the end, we hope to answer if biotech and pharma stocks really have exceeded the expectations of financial asset pricing models. If they have, we wish to highlight other factors that can explain the return.

The analysis builds on existing literature related to investments in health care stocks. Thakor et al. (2017) studied the stock returns of the biotech and pharma sector from 1930 to 2015 and found that the pharma sector delivered abnormal returns during the entire period except from 2000 to 2009. No outperformance was found for the biotech sector. Koijen et al. (2016) studied multiple sectors in the health care industry, including pharma and biotech, from 1960 to 2010 and found that firms highly engaged in medical R&D delivered positive abnormal returns. The authors suggest that investors in the health care industry should be compensated by a "medical innovation premium". Furthermore, Dong and Guo (2013) studied health care service stocks from 1967 to 2011 and found that they had abnormal returns. Overall, previous literature suggests that there exists positive abnormal returns in several health care sectors, including the biotech and pharma sectors. As some of these studies were conducted almost a decade ago, there are reasons to believe that investor perceptions towards biotech and pharma stocks have changed. The flow of new firms and increased focus on biotech amongst pharma firms suggest that there has been a major development. A paper written about biotech and pharma stocks even five years ago may be outdated. Our purpose is therefore to contribute to existing literature with more recent data and a wider geographical span.

The results from our analysis show a significantly positive alpha for the value-weighted biotech portfolio in Europe and the equally-weighted biotech portfolio in developed countries. More specifically, the portfolios delivered monthly abnormal returns of 0.407% and 0.627%, respectively, in the period from January 2010 to June 2022. Moreover, our analysis finds that biotech stocks fluctuated more with the market compared to pharma stocks. Thus, we can describe biotech stocks as cyclical and pharma stocks as defensive. We found that the value beta was negative for both sectors. A possible explanation is that both sectors are known for having assets in clinical development phases, which may not be reflected on the balance sheet. Additionally, the biotech portfolio is positively exposed to the size factor and negatively exposed to the profitability factor. This suggests that the biotech sector is tilted towards small-cap stocks that have weak profitability. The pharma portfolio is positively exposed to the investment factor, which suggests that the portfolio is tilted towards firms with conservative investment strategies.

We finish the introduction by describing the outline of the thesis. The upcoming section will describe the background and relevant literature for the thesis. Next, in section three, we will present the data selection process and portfolio construction. The fourth section will describe the applied methodologies, followed by the presentation of the results from our analysis in section five. The sixth section will include a further discussion of the main findings. Lastly, we will present the concluding remarks for our research question.

2 Background

In this chapter, we will start by describing the history of the pharma and biotech sectors. We will continue by presenting the definitions of the two sectors. Thereafter, we will discuss relevant aspects of investing in pharma and biotech stocks. We will touch upon sector investing, as well as abnormal returns and ethical aspects related to the sectors. Then, we will review existing literature, and finally we will present our research question and hypotheses.

2.1 The Shift Towards Biotech

The modern pharma industry has its roots in the 1800s. The foundation was to use chemical-based technology to treat diseases. Internal product development combined with in-licensing and acquisitions were strategies pursued by some of today's largest pharma firms, such as Johnson and Johnson and Eli Lilly and Co (Burns, 2020). The result is a 1.42 trillion dollar industry characterized by a number of large players with a wide geographical reach (Mikulic, 2022).

The inception of the biotech sector came in the late 1950s when scientists discovered the potential of genetic engineering and the recombinant DNA technique (rDNA). The method was to use the DNA code for a specific protein, integrate it into the DNA structure of a human or bacteria cell, and grow those cells to mass produce large amounts of the specified protein, which ultimately could be used as drugs. The rDNA technique laid the foundation for both Regeneron Pharmaceuticals and Genmab A/S, which are among the largest biotech firms today. In recent years, the biotech sector covers a much broader scope, including all firms that use innovative technology directed at developing drugs, diagnostics, vaccines, and other biotech products (Burns, 2020).

By the end of June 2022, there were over 1,300 biotech and pharma firms listed in developed countries[2]. Table 2.1 views the top 10 firms in each sector measured by market capitalization. Overall, we observe that the pharma firms are older and higher in market cap than biotech firms. With this in mind together with the history described above, we get the impression that pharma is close to a mature sector and biotech is more of an

[2]Developed countries excluding Australia, New Zealand and Japan.

emerging sector. We note that the US has a strong presence among firms in the biotech and pharma sector. In addition, Switzerland and Denmark have firms on both of the top 10 lists.

Table 2.1: Top 10 Stocks by Market Capitalization

Company	Market Cap	Founded	Country
Pharma Stocks			
Johnson and Johnson	USD 467bn	1887	US
Eli Lilly and Co	USD 308bn	1901	US
Pfizer Inc	USD 294bn	1942	US
Roche Holding AG	USD 275bn	1966	Switzerland
Abbvie Inc	USD 270bn	2012	US
Novo Nordisk A/S	USD 253bn	1931	Denmark
Merck and Co Inc	USD230bn	1970	US
AstraZeneca PLC	USD 204bn	1992	UK
Novartis AG	USD 203bn	1996	Switzerland
Biotech Stocks			
Regeneron Pharmaceuticals Inc	USD 64bn	1988	US
Moderna Inc	USD 56bn	2016	US
Lonza Group AG	USD 39bn	2002	Switzerland
BioNTech SE	USD 36bn	2019	US
Biogen Inc	USD 29bn	1997	US
Illumina Inc	USD 28bn	2000	US
Genmab A/S	USD 21bn	1998	Denmark
argenx SE	USD 20bn	2008	Belgium
Alnylam Pharmaceuticals	USD 17bn	2003	US
Novosymes A/S Inc	USD 16bn	2000	Denmark

But what about the future? The innovation of large pharma firms are increasingly attributed to biotech and the number of listed biotech firms has grown exponentially. There is a transition towards biomanufacturing in the health care sector, analogous to the industrial revolution's transition to machine manufacturing. Hence, some claim that a "bio-revolution" is on its way (Chui et al., 2020). The result is an increased blurry line as more and more firms use a combination of both technologies to deliver products and services. For instance, Roche Holding AG (hereby Roche) is Europe's largest pharma firm measured by market cap according to the database Refinitiv Datastream. Nonetheless, the firm brands itself as a biotech firm focused on personalized health care. A closer look into the annual reports reveals that Roche announced a restructuring towards biotech in 2006, which was followed by multiple acquisitions. Almost two decades later, the financial statements disclose that the majority of revenues are still generated by the pharma division. Roche serves as one of many examples of so-called biopharma, which increases the blurred line between biotech and pharma firms. Similar categorization issues are found for firms such as Bayer AG (2022) and Ipsen SA (2022).

2.2 Definition of Pharma and Biotech

Let us set biopharma aside for a moment and look at the main distinction between the two groups of firms. Pharma firms make drugs from chemicals[3], and biotech firms make drugs from living organisms, i.e. biologics. The former group of firms mainly focuses on new chemical entities (NCEs), which are small molecules that cause a biological process to start or stop. These chemicals are referred to as small because they can be taken orally and survive through the stomach and bloodstream till they reach the target organ or tissue successfully. Blood medicines, antidepressants, birth control pills, and painkillers are examples of chemical-based medicines. Biotech firms mainly focuses on larger molecules, which are vital for diseases where one wants to add or supplement a protein because of an organ's failure to produce it on its own. As these molecules are relatively big, they are destroyed in the stomach and poorly absorbed if taken orally. Biological products are therefore mostly injected. Therapeutic proteins, antibodies, peptides, and DNA and RNA molecules are examples of biotech products (Burns, 2020).

2.3 Investing in Pharma and Biotech

The biotech and pharma sector seem highly intriguing from a historical and scientific perspective. Nonetheless, this may not be enough to convince the average investor, whose main objective is to maximize returns (Bodie et al., 2020). Let us review the sectors from a financial perspective.

2.3.1 Sector Investing

Traditional finance theory argues there are two main categories of risk: systematic and unsystematic. Systematic risk applies to the whole market, while unsystematic risk is specific to a company or an industry (Burns, 2020). The CAPM argues that only systematic risk can be priced and that any unsystematic risk can be diversified away.

[3]Insulin was discovered in 1922 and is considered one of the oldest biotech products. Historically, insulin has been produced by pharma firms. Thus, it is more precise to say that pharma firms "mostly" make chemical drugs (Burns, 2020).

This only holds if investors are alike and can hold the market portfolio (Sharpe, 1964). In reality, we know that investors are different. Some will often deliberately structure their portfolios to accept considerable unsystematic risk in an attempt to obtain extraordinary returns (Malkiel, 2006). One way to achieve this is to invest in sector portfolios. These are not diversified as they solely focus on one area of the economy. Hence, sector portfolios exhibit high volatility and investors demand higher risk premiums. That is, investors demand compensation for tolerating a higher level of risk above the risk-free rate (Bodie et al., 2020). Portfolios constructed of biotech and pharma stocks will have unsystematic risks given their targeted sector exposure. Some investors argue that the unsystematic risk of biotech and pharma investments can provide positive abnormal returns. In the sections below, we will elaborate on some of the most common explanations.

2.3.2 Abnormal Returns of Pharma and Biotech Stocks

One of the most prominent explanations for why pharma and biotech stocks generate positive abnormal returns is the "medical innovation premium" (Koijen et al., 2016). Health care firms are exposed to government policies and interventions, such as patent laws, health programs, political reforms, subsidies, price constraints, and regulatory delays. Koijen et al. (2016) argue that these risks are more of a concern amongst biotech, pharma and health care equipment firms, compared to firms of other industries. Hence, the former group of firms should deliver positive abnormal returns.

Furthermore, some propose that huge R&D spending and long commercialization periods can explain the positive abnormal returns (Dong and Guo, 2013). The various clinical trials are capital intensive as they include multiple series of laboratory experiments, safety tests and approvals from the government. Furthermore, it takes fifteen years on average for a new medicine to pass all clinical trials (Golec and Vernon, 2009). Thus, an investor should be compensated for the accumulated R&D spending and for the long perspective of his or her investment.

Another explanation is that there are low hit ratios amongst the R&D projects in the health care sector. Hence, it is hard to predict which firms will succeed and which that will fail altogether (Bodie et al., 2020). There are many pitfalls along the way in the various clinical phases. In addition, not even experts or doctors are able to predict the release of a new blockbuster drug with sales over USD 1bn (Chen, 2022). For this reason, some investors may actively avoid these stocks. Hence, those that are willing to invest in biotech and pharma stocks can earn a premium.

Clearly, pharma and biotech firms are exposed to some of the same risks. However, there are some individual differences between the two sectors in terms of abnormal returns. The pharma sector can achieve abnormal returns over time as they tend to have steady cash flows regardless of the macroeconomic environment. This is due to the fact that most drugs have an almost inelastic demand as consumers will buy life-saving medicines regardless of the price (Maitland, 2002). It is also worth noting that these steady characteristics align with the description of defensive stocks (Chen, 2020). Furthermore, many drugs are protected by patents, which results in high profit margins. Also, pharma firms can finance their R&D projects with existing product sales, which makes them less exposed to external financing risk and failure of a project. In sum, the steadiness of pharma firms can result in a positive abnormal return over time.

Moreover, the biotech sector has proven to be less stable as firms typically do not generate earnings from existing product lines and are dependent on funding R&D costs. Biotech firms usually fund their R&D costs by external financing, mergers and aquistions (M&A) deals, or an alliance with another pharma or biotech firm (Thakor et al., 2017). The likelihood of these types of deals is influenced by the success rate of clinical trials, as well as the overall macroeconomic environment. Thus, the biotech sector can be considered a cyclical sector. In brief, biotech firms can achieve more extreme positive abnormal returns in cases of success, but also more extreme negative abnormal returns in cases of failure.

2.3.3 Ethical Aspects

Corporate Social Responsibility (CSR) has become an important dimension of business in recent years (Arsic et al., 2017). The principle of CSR is that firms have a responsibility to contribute to economic outcomes that meet societal expectations (Beal, 2014). Biotech is an emerging sector with the potential to revolutionize human lives by personalized health care and other advanced cures. In other words, biotech can contribute positively to the development of human civilization. Nonetheless, the biotech sector comes with a set of unknown impacts and ethical dilemmas. Cloning and the use of human stem cells for the production of organs are examples of two topics of intense debate (Fink, 2017). Blitz and Fabozzi (2017) argue that some investors actively avoid biotech stocks as they are considered sinful, which results in systematic underpricing. Hence, those that are indifferent to the ethical dilemmas will invest and be able to earn a premium.

There are also examples of ethical dilemmas in the pharma sector. One aspect is the direct-to-consumer advertising of prescription drugs, in which pharma firms advertise drugs to patients as opposed to specifically targeting health professionals. This has been a heated debate between the global pharma firm, GlaxoSmithKline (GSK) and the European Commission (EC). In 2001, GSK advertised directly to patients and claimed that it would increase the awareness of the available drugs in the market. This was not met with enthusiasm by the EC, who argued that the GSK's underlying goal was to increase sales (Metzl, 2007; Mintzes, 2002; Parker and Pettijohn, 2003). Direct-to-consumer advertising is illegal in the EU but legal in the US. (Mintzes, 2002). A possible implication of the legalised direct-to-consumer advertising in the US, is that pharma firms can convince healthy people that they have medical needs, so that they can increase sales and potentially investors' expected return.

2.4 Literature Review

Previous research on the stock performance of the biotech and pharma sector has had conflicting conclusions. In the next paragraphs, we will present a selection of the most relevant research articles and their main findings.

The first research paper we would like to highlight focuses on investments in the biopharma sector. Thakor et al. (2017) studied stock returns of 1,066 firms from 1930 to 2015 with the objective of understanding the risk-reward of investments in these two sectors. The researchers applied the CAPM and computed alphas for the whole time period and for every five-year period. They found a significant positive alpha for the pharma sector from 1930 to 2015, implying that the sector had exceeded investors' expected return. When studying the individual five-year periods, only three periods showed statistical significance at a 5% level or lower and with varying signs. 1955-1959 and 1970-1974 showed positive significance, while 1975-1979 showed negative. Thus, the pharma sector has not consistently outperformed the market in all time periods. For the biotech sector, researchers did not find any significant alphas with the exception of the five-year period 1986-1989. In this time interval, they found a significant negative alpha, which indicates that the biotech sector delivered poorer returns than expected. Furthermore, the paper found a consistently higher market beta for biotech than pharma. This implies that the former sector has higher systematic risk. The paper discusses several reasons for the difference in performance between the pharma and biotech sectors. First, biotech firms may not necessarily focus on generating earnings like pharma firms. They rather focus on large R&D investments that can be monetized in the future through patents, joint development deals, and mergers with big pharma firms. Thus, biotech firms are dependent on funding and may be more exposed to economic downturns. This can explain the higher market beta compared to pharma which typically relies on existing product lines.

The second research paper examinedreturns of firms that invest in medical R&D and the resulting growth of the health care sector. Koijen et al. (2016) studied five industries in the U.S. from 1961 to 2012, which included consumer goods, manufacturing, technology, health care and a residual category ("other"). The health care industry included medical equipment [4], pharmaceutical products [5] and health care services[6]. The primary research objective was to test the ability of the CAPM and the Fama-French Three-factor model in explaining variations in returns. Koijen et al. (2016) performed standard time-series regressions and found that firms highly engaged in medical R&D delivered annual abnormal returns of 4-6%. The authors suggest that investors in the health care industry should be compensated by a "medical innovation premium". They interpret the premium as compensation for government-induced profit risks. Further, they simulate the quantitative implications of the medical innovation premium on health care spending and on spending growth on medical R&D. The authors discover that the size of the health care industry would have expanded by 3% of GDP and R&D investments would have increased by 50% without the government risk.

The third relevant research article is by Dong and Guo (2013), who studied returns of the health care service sector in the US from 1967 to 2011. The definition of health care service

[4]Medical equipment includes x-ray, electromedicals, surgery, medical instruments and ophthalmic goods.

[5]Pharmaceutical products includes drugs, biological products, medical chemicals, pharmaceutical preparations, in vitro and in vivo diagnostics, as well as biological products, excluding biological diagnostics.

[6]Health care services includes offices and clinics of doctors, dentists, chiropractors, nursing and personal care facilities, hospitals and medical laboratories.

firms was similar to that of Koijen et al. (2016). The research objective was to identify the risk factors of health care stocks and the potential existence of positive Fama-French alpha. Dong and Guo (2013) performed panel data regressions with the Fama-French three-factor model, where both equally-and value-weighted portfolios were tested. They found that the market and size factors were significantly positive for health care stocks, which is an expected result according to the Fama-French model. However, the researchers found a significantly negative exposure to the value factor. This is inconsistent with the expectations of the model and implies that investors prefer low book-to-market stocks over high book-to-market stocks. Furthermore, one-third of the portfolios tested had significant non-zero alphas. Stocks in medical offices and clinics delivered positive alphas, which implies that investors received higher returns than expected after controlling for exposure to market, size and value. Whereas hospitals and personal care delivered negative alphas and thus poorer than expected. The researchers discuss that the possible reason for the non-zero alphas and the value anomaly is "the valuation biasness brought by patent and government regulation". They argue that the number of patents and lock-up periods of patents are reflected in high market prices rather than book values. Major research and development (R&D) investments, low hit ratio, and long industrialization periods serve as additional explanations of why investors appreciate growth stocks over value stocks in the health care industry. The discussion of R&D investments and patents is similar to the reflections Thakor et al. (2017) made in their study of biotech and pharma stocks.

2.5 Research Question

We are curious to explore the sectors further after reviewing the history and definitions, as well as the basis behind the potential abnormal returns of biotech and pharma. We do not know where our analysis will lead us in advance as previous literature has had conflicting conclusions regarding the existence of significant abnormal returns in the biotech and pharma sector. The following research question and constituting hypotheses will help us investigate this further:

Given the risks of biotech and pharma stocks, have the returns exceeded the expectations of financial asset pricing models?

- Hypothesis 1:

  H_0^1: *The biotech portfolio* ***does not*** *deliver significant abnormal returns.*

  H_A^1: *The biotech portfolio* ***does*** *deliver significant abnormal returns.*

- Hypothesis 2:

  H_0^2: *The pharma portfolio* ***does not*** *deliver significant abnormal returns.*

  H_A^2: *The pharma portfolio* ***does*** *deliver significant abnormal returns.*

The hypotheses are formulated on the basis of efficient markets, namely that current prices reflect all available information and expectations (Malkiel and Fama, 1970). Attractive investment opportunities are rarely obvious and will be competed away. Hence, our null hypotheses state that the portfolios will not deliver significant abnormal returns[7]. We will test the hypotheses by estimating alphas with the Fama French five-factor model without momentum. The main analysis will be of stocks in developed countries but we will also conduct continent analyses in North America and Europe. In addition, we will study results over different time-periods and of comparable sector indices.

[7]The efficient market hypothesis does not conclude that it is impossible for professional managers to earn higher than market returns. Mispricing can occur but not in predictable patterns that can lead to consistent outperformance (Malkiel and Fama, 1970)

3 Data

In this chapter, we will present the data selection process. First, we will present how we selected biotech and pharma stocks, and discuss the categorization dilemma of biopharma stocks. Then, we will explain the exclusion of other related sectors. Moreover, we will present how we selected the sector indices, regions, time periods, and risk factors. Lastly, we will elaborate on portfolio construction and data reliability.

3.1 Data Selection

We retrieve data from Refinitiv Datastream, Kenneth R. French Data Library and AQR Data Library. Refinitiv Datastream is a leading financial time series database that provides us with information about the firms in our analysis (Refinitiv, 2022). We categorize biotech and pharma stocks by the "subsector" of the well-known industrial classification benchmark (ICB) (FTSE Russel, 2022). Then, we download historical closing prices and market caps. Kenneth R. French Data Library and AQR Data Library provide us with historical benchmark returns of the systematic risk factors necessary to construct the multi-factor models.

We use monthly time-series data as this is preferred when analyzing data over longer time periods. This also creates a dynamic model (Wooldridge, 2012). We extract all data in United States Dollars (USD) to control for exchange rate fluctuations. In this way, we avoid investments becoming more or less profitable than the return in the local currency suggests.

3.1.1 Selection of Biotech Stocks

We select biotech stocks with ICB's subsector filter "Biotechnology". The subsector is a part of the sector filter “Pharmaceuticals and Biotechnology”, which again is part of the supersector filter “Health Care”. We manually screen all firms to get as precise data as possible. We discover that the sector contains a broad range of firms, from Intuitive Surgical (2022) that researches robotic-assisted surgery systems, to Bluebird Bio (2022) that develops cell and gene therapy for the treatment of cancer. We do not find any misclassifications and choose to include all firms.

3.1.2 Selection of Pharma Stocks

Similar to the selection of biotech stocks, we select pharma stocks with ICB's subsector filter "Pharmaceuticals". Naturally, the subsector is also part of the sector filter "Pharmaceuticals and Biotechnology", which again is part of the supersector filter "Health Care". Here, we also manually screen all firms. First, we notice Microalliance Group Inc. (2022), a holding company whose primary business is the distribution of coffee, tea and spirit products in China. We decide to exclude the firm from our data set as biotech is not the main business of the firm. Next, we discover Alkaloid (2022), a producer of medications, cosmetics and chemical products in North Makedonia. We exclude the firm as North Macedonia is not part of UN's list of developed countries (UN, 2022). Finally, we notice Biogen (2022), a biotech firm developing customized and digital medicine in neuroscience. As Biogen Inc is a biotech firm and not a pharma firm, we move it to the list of biotech firms.

3.1.3 Categorization Dilemma of Biopharma Stocks

Biopharma is another term that complicates the classification of biotech and pharma firms. The term describes companies that are using both biological and chemical sources in R&D projects. ICB has not classified biopharma as an individual subsector. Thus, there exist biopharma firms in both the biotech subsector and the pharma subsector. Hoffman (2022), Bayer AG (2022) and Ipsen SA (2022) are examples of biopharma that are categorized as pharma firms while conducting biotech research. The biopharma firms lead to an overlap between the two subsectors, which can increase the similarities between our constructed sector portfolios.

3.1.4 Other Related Sectors

Cannabis

There exists a third subsector in the sector "Pharmaceuticals and Biotechnology", namely "Cannabis Producers". There are conflicting views among developed countries on whether cannabis is an accepted medical treatment or not. No national government in Europe favors legalizing cannabis sales, and there are harsh penalties for illegal supply of cannabis (EMCDDA, 2022). Conversely, cannabis is legal in 37 states in the US (NCSL, 2022). We choose to exclude cannabis from our analysis to avoid bias in the continent portfolios.

Nutritional Supplements

We also find it necessary to clarify that nutritional supplement producers are not part of the pharma subsector. The nutritional supplement producers are positioned between traditional foods and medicines, what some call the "pharma-nutrition interface" (Georgiou et al., 2011). CVS Health is an example of a firm that sells both pharma drugs and nutritional supplements (Heart Health, 2021). The regulatory frameworks in Europe and the US distinguish between pharma firms and nutritional supplement firms. The frameworks state that the primary goal of pharma is to treat, cure or prevent disease, while the primary goal of nutritional supplements is to maintain or improve health (European Commission, 2003; U.S. Food and Drug Administration, 2005). For this reason, we do not include nutritional supplements in our pharma portfolio.

Herbal Medicine

Lastly, we find it necessary to clarify that producers of herbal medicine are not part of the pharma subsector. The primary goal of herbal medicine is to maintain health and treat various diseases. It has become an important building block of alternative medicine and some claim it to be a rival of pharmaceutical drugs (Lakshmana Rao and Suneetha, 2010). However, herbal medicine does not have the same level of scientific validation. Herbal medicines do not have any legal standards in developed countries (Sukhdev et al., 2008). Hence, we choose to exclude herbal medicine from our analysis.

3.1.5 Selection of Sector Indices

In our main analysis, we also wish to include a study of two comparable sector indices, namely the S&P 500 Pharmaceuticals and the S&P 500 Biotechnology. The S&P 500 Market index is one of the most commonly used benchmarks in the world. Hence, we believe that its sector indices can serve as accurate performance measurements of biotech and pharma stocks and be useful in comparative analyses. The S&P 500 sector indices are value-weighted and quarterly rebalanced based on the number of shares that are available for trading (S&P Dow Jones Indices, 2022).

3.1.6 Selection of Regions

Biotech and pharma firms are present in some way in all countries and markets across the world. We choose to focus on developed countries. We use the United Nations' (UN) classification of developed economies. The classification only includes countries with gross national income (GNI) per capita over a certain level. It also takes into account a human assets index and an economic vulnerability index (UN, 2022). We split the list of developed economies into two regional groups, namely North America and Europe. We choose to exclude Japan, Australia and New Zealand because of the periods of economic stagnation and missing data on historical stock returns and market capitalization. Note that the retrieval of the firms is based on the country in which the stocks are listed and not the location of the headquarters.

There are several reasons why we choose to focus on developed countries. First, we want to compare countries with similar income per capita, level of industrialization, technological advancement, infrastructure and political stability. For many investors developed countries are therefore considered safer investment destinations (Perry, 2022). Second, developed countries tend to have more similar economic growth rates[8] (Majaski, 2022). These countries also tend to have similar health, nutrition and human development histories. Measures such as stature, life expectancy and morbidity have evolved in the same direction and have been supported by the economic growth that has occurred in the developed countries. Third, most developed countries have a universal health care system so that public spending and research subsidies are guaranteed at a certain level (Floud et al., 2011). Nonetheless, there are differences in terms of political and economic risk among the developed countries, which is why we choose to also make regional portfolios.

3.1.7 Selection of Time Period

We select 31.12.2009-31.06.2022 as our time period. We limit the number of years in our analysis due to several reasons. First, we want to focus on the accelerated technological development of the last decade. Second, the number of listed firms within each sector has increased during the last few decades, which can result in data skewness. Third,

[8] The economic growth rate is the change in the gross domestic product (GDP) and is an indicator of the general direction of a nation's economy (UN, 2022).

our selected time span enables us to explore biotech and pharma stocks during different macroeconomic conditions, such as Covid-19 and the recent period of economic uncertainty.

3.1.8 Selection of Risk Factors

As mentioned we retrieve the Fama-French factor returns from the Kenneth R. French Data Library. We retrieve five factors, namely market (MKT), size (SMB), value (HML), profitability (RMW) and investment (CMA). The database provides region-specific factors necessary to construct the multi-factor models for our analysis. We retrieve the factors for developed countries, North America and Europe. Furthermore, we retrieve two risk factor returns from AQR Data Library, namely betting against beta (BAB) and quality minus junk (QMJ). We retrieve factors for developed countries only, as this is the only option available.

3.2 Portfolio Construction

We construct our portfolios[9] according to sectors and regions. The sectors in our analysis include biotech and pharma, and the regions include developed countries, North America and Europe. The main analysis examines value-weighted portfolios. Hence, returns of larger (smaller) firms have more (less) weight in the portfolios as opposed to equally-weighted. There are multiple reasons behind the choice of value-weighted portfolios for our main analysis. First, it seems sensible as large firms tend to be more liquid than small firms. Second, previous literature on our topic has applied value-weighting (Koijen et al., 2016; Dong and Guo, 2013; Thakor et al., 2017). Third, most indices are value-weighted. Thus, also many funds are close to value-weighted as they often use indices as benchmarks.

Moreover, we chose monthly rebalancing in our main analysis as this is common in academic research. We include annually rebalanced portfolios and equally-weighted portfolios in our robustness analysis. This way we can gain insights of a less frequent rebalancing strategy and the consequences of assigning equal weights to each firm. The following paragraphs will describe the portfolio construction in detail.

[9]Note that the returns of the sector indices were retrieved value-weighted. Hence, these are not included in the portfolio construction.

3.2.1 Calculation of Stock Returns

We define a set $\mathcal{A}$ which contains all the considered stocks, and a set $\mathcal{T}$ of the considered months. Every stock a has a closing price p_{at} at the end of month t. We find that it was not necessary to make any adjustments as stock splits and dividends are already accounted for (Reuters, 2008). The return of stock a in month t can then be formulated as

$$x_{at} = \frac{p_{at}}{p_{a(t-1)}} - 1, \qquad \forall\, a \in \mathcal{A},\ \forall\, t \in \mathcal{T} \setminus \{t_1\}. \tag{3.1}$$

Note that the return is not defined for the first month in our analysis period.

3.2.2 Calculation of Weights

We define a set $\mathcal{R}$ of the considered regions and a set $\mathcal{S}$ of the considered sectors. Then, we define a subset $\mathcal{A}_{rst} \subset \mathcal{A}$ of stocks in the portfolio corresponding to region $r \in \mathcal{R}$ and sector $s \in \mathcal{S}$. Since some of the stocks were listed later than the start of our analyzed period, the set A_{rst} also changes with the month $t \in \mathcal{T}$. Every stock a has a market cap m_{at} at month t. The value-weight of stock a at time t can then be written as

$$w^V_{at} = \frac{m_{a(t-1)}}{\sum_{a' \in \mathcal{A}_{rs(t-1)}} m_{a'(t-1)}}, \quad \forall\, r \in \mathcal{R},\ s \in \mathcal{S},\ a \in \mathcal{A}_{rst},\ t \in \mathcal{T}, \tag{3.2}$$

and the equally-weight of stock a in month t is formulated as

$$w^E_{at} = \frac{1}{|\mathcal{A}_{rs(t-1)}|}, \quad \forall\, r \in \mathcal{R},\ s \in \mathcal{S},\ a \in \mathcal{A}_{rst},\ t \in \mathcal{T}. \tag{3.3}$$

3.2.3 Calculation of Portfolio Weighted Returns

The value-weighted return in month t for the portfolio corresponding to region r and sector s is derived as

$$R^V_{rst} = \sum_{a \in \mathcal{A}_{rst}} w^V_{at} x_{at}, \quad \forall\, r \in \mathcal{R},\ s \in \mathcal{S},\ t \in \mathcal{T}. \tag{3.4}$$

The equally-weighted return in month t for the portfolio corresponding to region r and sector s is expressed as

$$R^E_{rst} = \sum_{a \in \mathcal{A}_{rst}} w^E_{at} x_{at}, \quad \forall\, r \in \mathcal{R},\ s \in \mathcal{S},\ t \in \mathcal{T}. \tag{3.5}$$

Table 4.1 shows a summary of the sets and parameters applied in the portfolio construction.

Table 3.1: Summary of Portfolio Construction Symbols

	Explanation	**Elements**
Sets		
$\mathcal{A}$	Set of stocks a	All stocks
$\mathcal{T}$	Set of time periods t	All months
$\mathcal{R}$	Set of regions r	Developed Countries, North America, Europe
$\mathcal{S}$	Set of sectors s	Biotech, Pharma
$\mathcal{A}_{rst} \subset \mathcal{A}$	Set of stocks in region r and sector s at time t	
Parameters		
p_{at}	Closing price of stock a at time t	
x_{at}	Return of stock a at time t	
$m_{a(t-1)}$	Market capitalization of stock a at time $t-1$	
w^V_a	Value-weight of stock a at time t	
w^E_a	Equal-weight of stock a at time t	
R^V_{rst}	Value-weighted portfolio return at time t in region r and sector s	
R^E_{rst}	Equally-weighted portfolio return at time t in region r and sector s	

3.3 Data Reliability

We also find it necessary to discuss the reliability of our data set. That is, whether the data is complete and accurate. We will discuss our concerns of the Refinitiv Datastream, the extracted risk factors and the portfolios' industry composotions in the following sections.

3.3.1 Refinitiv Datastream

First, there is a possibility that not all listed firms have their data updated in Refinitiv Datastream. Hence, our portfolios may not include all the listed firms within a region. Nevertheless, we do not see this as a big issue as the database is the longest-serving database for financial analysis and remains the market-leading product for sector research (Derasse, 2017). Second, there is a possibility that not all biotech and pharma firms are connected to the ICB subsector filter. This concern has a basis in our manual screening, in which we found several misplacings. However, we do not consider this a big issue either as we detected a few misplaces and corrected these. In sum, we believe Refinitiv Datastream is the most optimal database to gather relevant data.

3.3.2 Kenneth R. French Data Library and AQR Data Library

Another concern is the difference in geographical reach between the stocks in our portfolios and the systematic risk factors. Table 3.2 views the continents and respective countries that the Fama-French and AQR factors provide. The lists of the two databases are identical except that AQR also includes Israel. Our analysis applies factors of developed countries, North America and Europe. We notice that the list of developed countries is shorter than the one provided by the UN. E.g., Slovenia, Poland and Croatia are defined as developed countries by the UN but not included on the list. We also notice that Singapore and Hong Kong are included on the list even though these are not defined as developed countries according to the UN. Furthermore, we observe that the European list of countries is shorter than the actual scope. To summarize, the continent-specific market effects of the retrieved factors are not fully consistent with the composition of our portfolios. This might affect the detail level of our analysis.

Table 3.2: Kenneth French' and AQR's Divisions of Regions

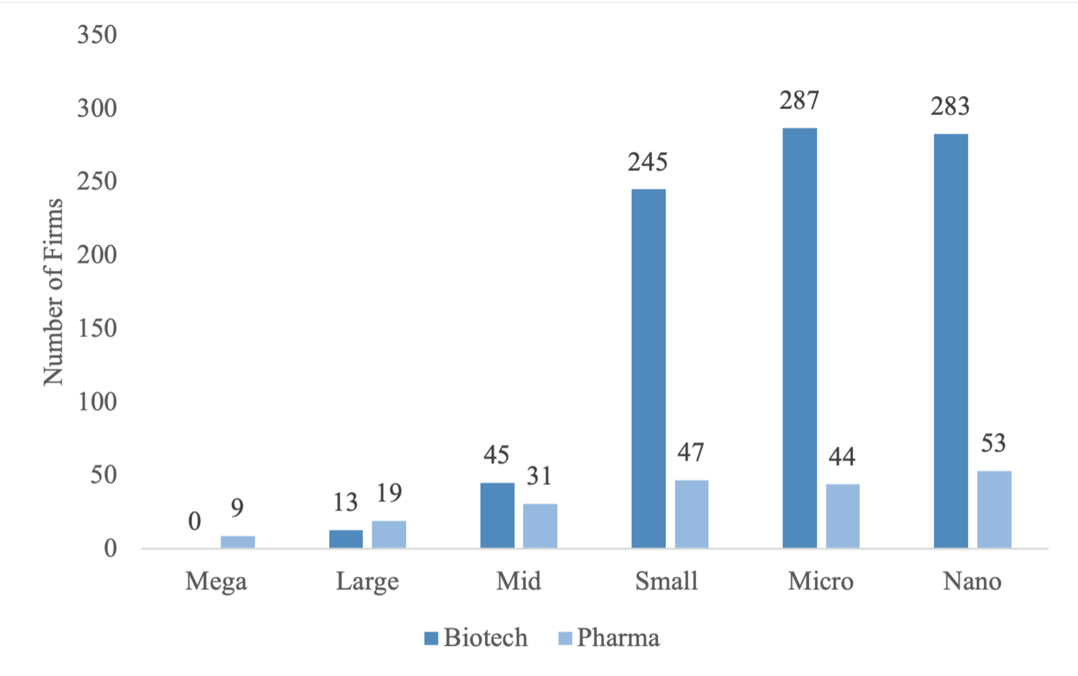
Country	Developed	Developed ex US	Europe	Japan	Asia Pacific ex Japan	North America
Australia	✓	✓			✓	
Austria	✓	✓	✓			
Belgium	✓	✓	✓			
Canada	✓	✓				✓
Switzerland	✓	✓	✓			
Germany	✓	✓	✓			
Denmark	✓	✓	✓			
Spain	✓	✓	✓			
Finland	✓	✓	✓			
France	✓	✓	✓			
Great Britain	✓	✓	✓			
Greece	✓	✓	✓			
Hong Kong	✓	✓			✓	
Ireland	✓	✓	✓			
Israel (AQR)	✓	✓	✓			
Italy	✓	✓	✓			
Japan	✓	✓		✓		
Netherlands	✓	✓	✓			
Norway	✓	✓	✓			
New Zealand	✓	✓			✓	
Portugal	✓	✓	✓			
Sweden	✓	✓	✓			
Singapore	✓	✓			✓	
Unites States	✓					✓

3.3.3 Industry Composition

Developed Countries

Figure 3.1 illustrates how stocks in the biotech and pharma sectors in developed countries are distributed between mega-cap, large-cap, mid-cap, small-cap, micro-cap, and nano-cap firms as of June 2022. We observe that the majority of biotech stocks are small-, micro- or nano-cap, while the pharma firms has a more even distribution. In all three categories, the biotech sector has more than five times as many firms as the pharma sector. We also notice that 9 of the pharma firms are mega-cap, while biotech has none.

Figure 3.1: Developed Countries Market Cap Classification and Number of Firms

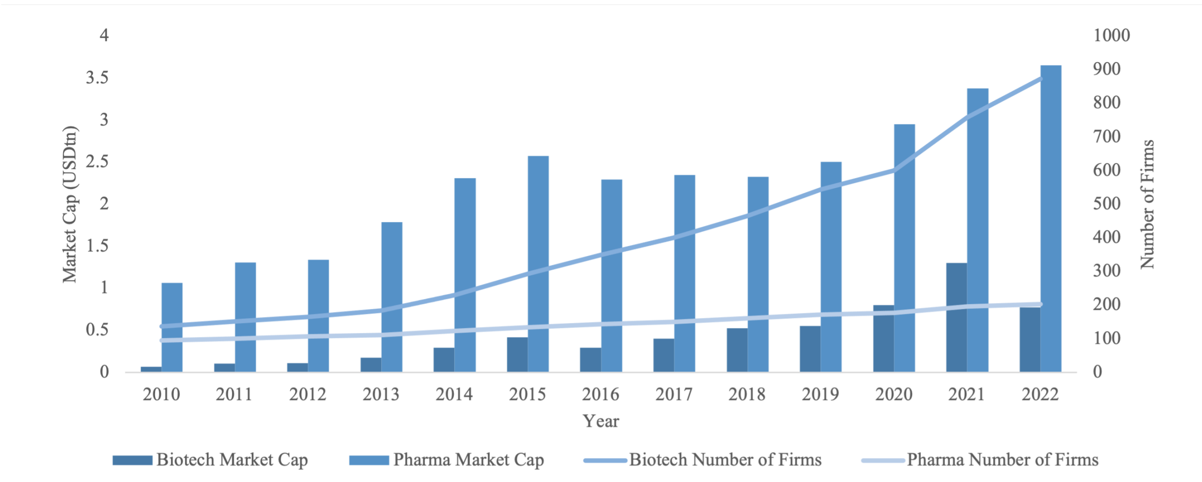


We also raise a concern regarding the difference in market cap and the number of firms across the various regions and sectors. Figure 3.2 presents the skewness of the firms across developed countries from 2010 to 2022. According to this statistic, we see clear differences in the industry composition between biotech and pharma, despite having the same number of observations (n=150). First, we observe that the pharma sector in developed countries has a substantially higher total market cap than biotech over the entire sample period. In June 2022, the pharma sector had a total market cap of USD 3.65tn, making up 83% of the total average market cap of biotech and pharma. However, we note that the biotech sector had a substantial increase in market cap in 2021, climbing by 63% from 2020. This growth can be linked to firms that successfully developed Covid-19 vaccines, such as Pfizer, BioNTech and Moderna (Balfour, 2022).

Furthermore, we see a difference in the number of firms between the biotech and pharma sectors. In June 2022, the number of pharma firms were 203 compared to biotech firms of 873. This seems reasonable as pharma can be considered a mature sector, while biotech an emerging sector. It also aligns with the median age of the firms in the two sectors. Considering the development in number of firms, the pharma sector has clearly had the lowest increase from 2010 to 2022, with only 116% compared to 541% for biotech firms. This can be related to the fact that many pharma firms actively pursue mergers and acquisition strategies (Hayes, 2022).

To summarize, the difference in market cap and the number of firms can lead to sector-related biases in our results. The pharma sector consists of relatively larger firms compared to the biotech sector. Thus, large pharma firms can impact the performance of other firms in the sector as it is hard to capture market shares from these. In addition, large pharma firms will have a higher impact on the performance of the value-weighted portfolio.

Figure 3.2: Developed Countries Market Cap and Number of Firms



Europe and North America

Figure 3.3 and 3.4 presents the skewness of the firms and market caps in North America and Europe from 2010 to 2022. First, we observe that the pharma sector has a substantially higher market cap than the biotech sector as observed at the developed country level. Second, we observe continent differences. North America has a larger market cap and more firms than Europe. The pharma and biotech sectors in Europe only account for 36% and 23% of the total market cap for developed countries, respectively. This indicates that North America is the major contributor to the overall trends in the combined sector portfolios of developed countries. This can impose a problem as the different regions may have different biases and risks.

Figure 3.3: North America Market Cap and Number of Firms

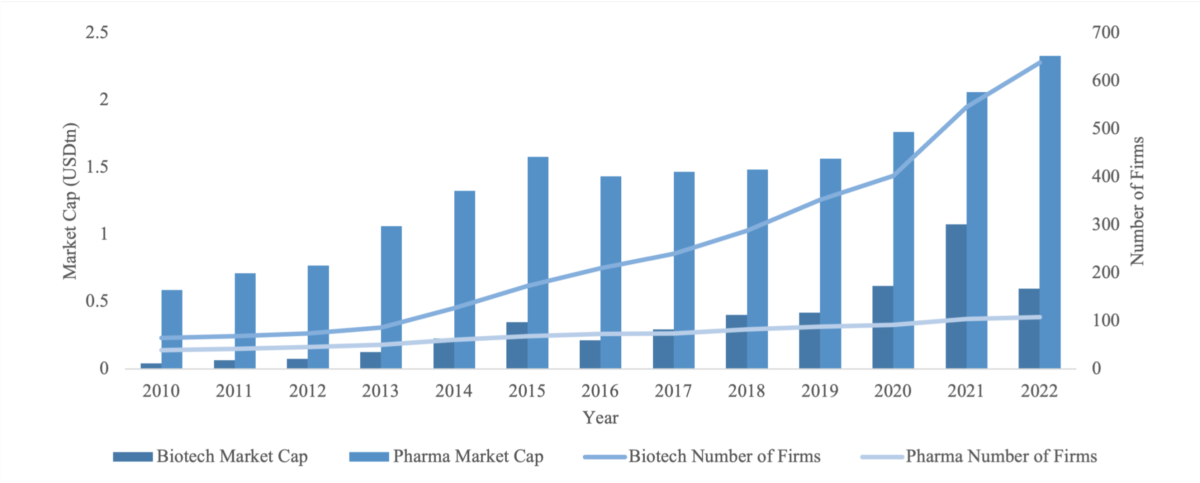
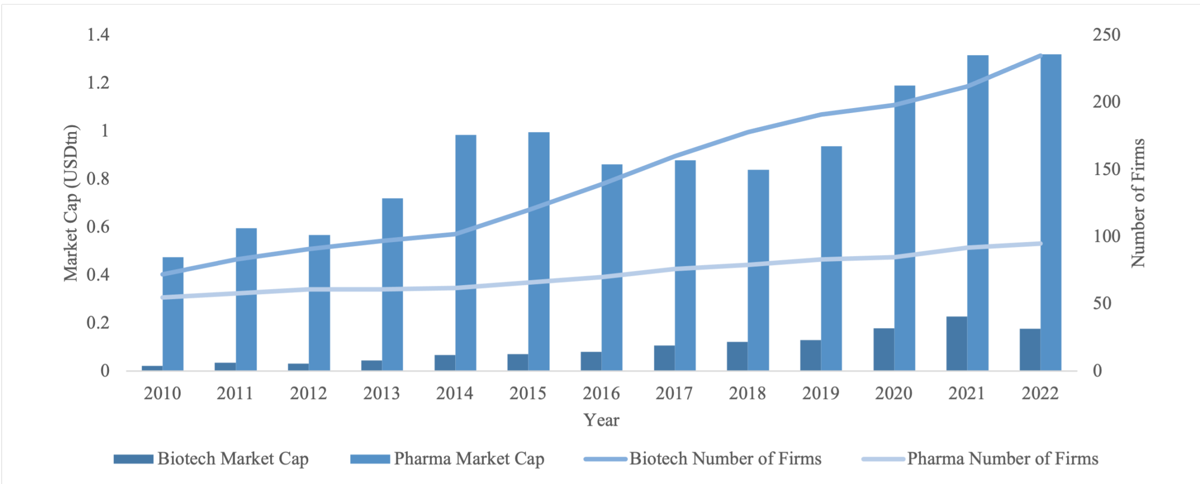


Figure 3.4: Europe Market Cap and Number of Firms



4 Methodology

In this section, we will describe the methodology applied to detect potential abnormal returns in the biotech and pharma portfolios. Our main analysis applies the Fama-French five-factor model without momentum to estimate the alphas. We will elaborate on the motivation behind this model in section 4.7. However, our robustness analysis includes results with other alternative factor models, namely the Fama-French three-factor model, four-factor (Carhart) model, and five-factor model without momentum. These are all extensions of the Capital Asset Pricing Model (CAPM) and a result of the emergence of other risk factors. We will not use the CAPM in our analysis as the model has been criticized due to its simplicity and lack of explanatory variables (Fama and French, 2004). However, we will start by presenting the CAPM and the other factor models, as these laid the foundation of the Fama-French five-factor model.

4.1 CAPM and Jensen's Alpha

The CAPM was developed in the early 1960s by (Sharpe, 1964; Treynor, 1961; Lintner, 1965; Mossin, 1966). The rationale of the model is that investors only should be compensated for holding a higher systematic risk. The idea was that not all risks should affect asset prices. More specifically, a risk that can be diversified when held together with other investments, is not a risk at all (Bodie et al., 2020). There are four assumptions that need to be fulfilled in order for the CAPM to hold. These are that investors hold diversified portfolios, there are single-period transaction horizons, investors can borrow and lend at a risk-free rate of return, and there is a perfect capital market. If the CAPM holds and fully explains the expected return, the alpha should be zero (Bodie et al., 2020).

Jensen's alpha (hereby alpha) was introduced in 1969 as a continuation of the CAPM. The alpha is the average return on a portfolio or investment in excess of what is predicted by the CAPM. If the portfolio or investment is fairly priced, the actual return will match the expected return provided by CAPM and the alpha will be zero. The asset pricing model provide a significantly positive (negative) alpha if a portfolio or investment performs significantly better (worse) than the market (Jensen, 1969). If the wrong factors are utilized, the alpha may instead reflect a pricing error (Jarrow and Protter, 2011).

The equation is as follows:

$$R_{it} - R_{ft} = \alpha_i + \beta_{iMKT}(R_{mt} - R_{ft}) + \epsilon_{it} \tag{4.1}$$

4.2 Fama-French Three-Factor Model

In 1993, Fama and French proposed a three-factor model as a further extension of the CAPM. The model accounts for two company-specific risk factors, namely SMB and HML. SMB is short for "Small Minus Big" and mimics a portfolio that is long in small-cap stocks and short in large-cap stocks. While HML refers to "High Minus Low" and mimics a portfolio that is long in high book-to-market stocks ("value stocks") and short in low book-to-market stocks ("growth stocks"). In other words, the factors measure the premium of size and value, respectively (Fama and French, 1993). The betas in the model measures the portfolio's exposure to the factors[10]. The three-factor model is built in the following way:

$$R_{it} - R_{ft} = \alpha_i + \beta_{iMKT}(R_{mt} - R_{ft}) + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + \epsilon_{it} \tag{4.2}$$

4.3 Carhart Four-Factor Model

The four-factor model was proposed by Mark Carhart in 1997. It adds a fourth factor to the Fama-French three-factor model, namely "MOM", which is short for momentum. The justification for adding this factor was its ability to measure consistency in performance. That is, stocks that had performed well or poorly in the recent past also continued to do so. As a result, the MOM factor mimics a portfolio that goes long in winners and short in losers, measured in recent stock returns (Carhart, 1997). The four-factor model is as follows:

[10]The betas also measures the portfolio's exposure to the factors in the Carhart four-factor model, the Fama-French five-factor model with and without momentum, as well as the seven-factor model. We will not repeat the beta explanation in every model explanation. There is a summary of all symbols in Table 4.1.

$$R_{it} - R_{ft} = \alpha_i + \beta_{iMKT}(R_{mt} - R_{ft}) + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + \beta_{iMOM}MOM_t + \epsilon_{it} \quad (4.3)$$

4.4 Fama-French Five-Factor Model

In 2014, a few decades after introducing the three-factor model, Fama and French added two new factors, RMW and CMA. RMW is short for "Robust Minus Weak" and mimics a portfolio that goes long in firms with robust profitability and short in the ones with weak. CMA refers to "Conservative Minus Aggressive" and represents a portfolio that goes long in firms with low investment activity and short in the ones with aggressive. In other words, the factor measures the premium of profitability and investment strategy, respectively (Fama and French, 2015). The Fama-French five-factor model is structured as follows:

$$\begin{aligned} R_{it} - R_{ft} = \alpha_i + \beta_{iMKT}(R_{mt} - R_{ft}) + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t \\ + \beta_{iRMW}RMW_t + \beta_{iCMA}CMA_t + \epsilon_{it} \end{aligned} \quad (4.4)$$

4.5 Fama-French Five-Factor Plus Momentum

The Fama-French five-factor model also comes with the momentum factor from the Carhart model. We want to include this in our robustness analysis to examine whether this model can further explain the performance of the biotech and pharma portfolios. The five-factor model plus momentum is structured in the following way:

$$\begin{aligned} R_{it} - R_{ft} = \alpha_i + \beta_{iMKT}(R_{mt} - R_{ft}) + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t \\ + \beta_{iMOM}MOM_t + \beta_{iRMW}RMW_t + \beta_{iCMA}CMA_t + \epsilon_{it} \end{aligned} \quad (4.5)$$

4.6 Seven-Factor Model

We also construct a seven-factor model with inspiration from Norges Bank Investment Management (Dahlquist and Ødegaard, 2018). The model adds two more factors to the Fama-French five-factor model, namely BAB and QMJ. BAB is short for "Betting Against Beta" and represents a portfolio that goes long in low-beta assets and short in high-beta assets (Frazzini and Pedersen, 2014). QMJ is short for "Quality Minus Junk" and represents a portfolio that goes long in high-quality stocks and shorts low-quality stocks (Asness et al., 2019). The seven-factor model is structured as follows:

$$\begin{aligned} R_{it} - R_{ft} = \alpha_i + \beta_{iMKT}(R_{mt} - R_{ft}) + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t \\ +\beta_{iRMW}RMW_t + \beta_{iCMA}CMA_t + \beta_{iBAB}BAB_t + \beta_{iQMJ}QMJ_t + \epsilon_{it} \end{aligned} \tag{4.6}$$

Table 4.1 shows a summary of the symbols applied in the models.

Table 4.1: Summary of Model Symbols

	Full form	**Explanation**
Risk Factors		
SMB_t	Small Minus Big	Excess return of small-cap firms over big-cap firms at time t.
HML_t	High Minus Low	Excess return of high book-to market firms over low book-to-market firms at time t.
MOM_t	Momentum	Excess return of winner firms over loser firms at time t.
RMW_t	Robust Minus Weak	Excess return of firms with robust profitability over firms with weak profitability at time t.
CMA_t	Conservative Minus Agressive	Excess return of firms with conservative investment strategy over firms with agressive investment strategy.
BAB_t	Betting Against Beta	Excess return of low-beta firms over high-beta firms at time t.
QMJ_t	Quality Minus Junk	Excess return of quality firms over junk firms at time t.
Betas		
β_{iSMB}		Portfolio i's exposure to the size factor.
β_{iHML}		Portfolio i's exposure to the value factor.
β_{iMOM}		Portfolio i's exposure to the momentum factor.
β_{iRMW}		Portfolio i's exposure to the profitability factor.
β_{iCMA}		Portfolio i's exposure to the investment factor.
β_{iBAB}		Portfolio i's exposure to the betting against beta factor.
β_{iHML}		Portfolio i's exposure to the quality factor.
Other		
R_{it}		Return on portfolio i at time t.
R_{ft}		Return on one month risk-free rate f at time t.
α_i		Abnormal return of portfolio i.
ϵ_{it}		Error term of portfolio i at time t.

4.7 Model Motivation

As mentioned, we apply the Fama-French five-factor model without momentum to estimate the alphas in our main analysis. We choose this model as it explains the return by five well-tested systematic risk factors. An alpha will occur due to risk which is not explained by the model. Based on the idea that the five-factor model capture all systematic risk, the alpha will represent unsystematic risk. Consequently, any significant alpha might be interpreted as firm-specific risk (Fama and French, 2015). Additionally, the Fama-French risk factors are widely used by researchers and investors. We believe the recognition of the model will make our thesis more intuitive and comparable to previous research.

4.8 Model Testing

To verify that the regression coefficients are the best linear unbiased estimators (BLUE), the five Gauss-Markow assumptions for time series must be satisfied. These are i) linear in parameters, ii) no perfect collinearity, iii) zero conditional mean, iv) homoscedasticity, and v) no serial correlation (Wooldridge, 2012). It is not necessary to test for assumptions i) and ii) as we employ independent factors that already have been shown to significantly affect stock returns (Carhart, 1997). We assume a zero conditional mean, that is the expected value of the error at time t is uncorrelated with each explanatory variable in all time periods (Wooldridge, 2012). Further, we test for heteroskedasticity as the presence of this gives incorrect standard errors and test statistics. All portfolios were homoscedastic according to the Breush-Pagan test. Hence, we did not need to adjust the portfolios by calculating robust standard errors. We tested for autocorrelation with the Breush-Godfrey test. None of the portfolios had test results that indicated autocorrelation.

In order to use the standard errors and test statistics, we also need to test for normality. We create histograms for all portfolios and confirm that the sample mean is centered around zero. In addition, we create QQ-plots and note that the points seem to form a relatively straight line, suggesting that the residuals are normally distributed for all portfolios. Lastly, we need to check for stationarity. A time series is stationary when the marginal and all joint distributions are invariant across time (Wooldridge, 2012) . We apply the Dickey-Fuller test for unit root and confirm that all portfolios are stationary.

The outputs from all the tests can be found in the appendix.

4.9 Model Weaknesses

We begin by discussing the general weaknesses of the factor models. All of the asset pricing models are capable of being misspecified. The factor models start out by assuming that the betas remain constant over time. Without detecting dynamic changes in the factor exposures, our analysis only estimates static exposures. Second, there are costs associated with implementing the factor model's exposures. Achieving the desired exposures requires a rebalancing of the portfolio, which in turn, induces transaction costs. We assume that no expense is incurred in obtaining the exposures. The alpha estimations would change if these costs were taken into consideration (Kapadia and Paye, 2014).

Furthermore, Fama and French (2015) argues that the five-factor model explains the variations in stock returns better than the three-factor model as the profitability and investment activity risk factors also prove to be important. However, the five-factor model also has its limitations. Fama and French (2015) raise a concern related to adding more explanatory variables to the model. One issue is that the HML factor becomes redundant when the RMW and CMA factors are included, particularly if parsimony is a concern. This is because the average stock return is captured by the other risk factors. Thus, the model performs equally well with and without the HML component if the only goal is to estimate abnormal returns. Another issue is that the five-factor model will provide a correlation between the explanatory variables if the momentum factor is included. This may weaken the explanatory power of the regression (Fama and French, 2015).

5 Analysis

In this chapter we will present the analysis that aims to answer the following research question and constituting hypotheses:

Given the risks of biotech and pharma stocks, have the returns exceeded the expectations of financial asset pricing models?

- Hypothesis 1:
  H_0^1: *The biotech portfolio* ***does not*** *deliver significant abnormal returns.*
  H_A^1: *The biotech portfolio* ***does*** *deliver significant abnormal returns.*
- Hypothesis 2:
  H_0^2: *The pharma portfolio* ***does not*** *deliver significant abnormal returns.*
  H_A^2: *The pharma portfolio* ***does*** *deliver significant abnormal returns.*

We will begin by presenting the descriptive statistics for the sector portfolios and the market proxies. Thereafter, we will present the regression results with the chosen main model, i.e., the Fama-French five-factor model. The main analysis is centered around the portfolios of stocks in developed countries. We do analyses on regional levels, over different time periods and on comparable indices to gain further insights. At the end of the chapter, we will present a robustness analysis with alternative factor models, as well as annually rebalanced and equally-weighted portfolios with the main model.

5.1 Descriptive Analysis

In this section, we will provide a descriptive analysis of the biotech portfolios, pharma portfolios and market proxies on a continent- and time period level. We also add the sector indices as it is a part of our main analysis. The descriptive analysis includes discussions of Sharpe ratios, cumulative returns and returns at different percentiles.

5.1.1 Descriptive Statistics

Table 5.1 presents the descriptive statistics for the full time period, as well as the first 6 years and last 6.5 years.

Table 5.1: Descriptive Statistics

Statistics	Sharpe Ratio	Mean Return	Std.Dev	Min	Max
Panel A: Full Time Period					
Developed countries					
Biotech	0.122	0.867	6.791	-21.067	17.069
Pharma	0.193	0.760	3.740	-9.077	10.454
Market proxy	0.184	0.782	4.252	-13.650	13.350
North America					
Biotech	0.117	0.960	7.888	-23.692	21.168
Pharma	0.220	0.881	3.818	-9.072	11.969
S&P 500 Biotech	0.221	1.235	5.404	-13.683	15.381
S&P 500 Pharma	0.215	0.853	3.793	-8.518	11.243
Market Proxy	0.235	1.013	4.313	-13.970	13.330
Europe					
Biotech	0.167	0.896	5.145	-16.222	11.821
Pharma	0.136	0.598	4.123	-10.496	10.331
Market proxy	0.112	0.562	5.009	-15.320	16.630
Panel B: First 6 Years					
Developed countries					
Biotech	0.295	1.844	6.239	-10.231	14.609
Pharma	0.281	1.013	3.596	-9.077	8.230
Market proxy	0.188	0.779	4.142	-9.530	10.010
Panel C: Last 6.5 Years					
Developed countries					
Biotech	-0.017	-0.034	7.186	-21.067	17.069
Pharma	0.122	0.527	3.876	-8.124	10.454
Market proxy	0.190	0.786	4.379	-13.650	13.350

Note: The Sharpe ratio is the average return minus the average risk-free rate, divided by the average standard deviation. Mean return is the average return of all stocks in the relevant portfolio. Standard deviation is the average amount of variability in all stocks in the relevant portfolio. The min (max) return is the smallest (largest) return observed in a the relevant portfolio.

Sharpe Ratios

We begin by studying the Sharpe ratios for the full time period. The North American market proxy is the most attractive portfolio based on the Sharpe ratio of 0.235%. In other words, the portfolio delivers the highest average return per unit of risk. This is in accordance with the CAPM, which considers the market portfolio to be the optimal choice (Bodie et al., 2020).

In developed countries and Europe, the sector portfolios deliver the highest risk-adjusted returns. The pharma portfolio and biotech portfolio are superior in terms of Sharpe ratio in developed countries and Europe, respectively. This is in line with the observations of Thakor et al. (2017) in the pharma sector. Nonetheless, these findings contradict with the

CAPM. In sum, neither of the sector portfolios or market proxies consistently deliver the highest Sharpe ratios across regions. There appear to be regional differences among the sectors and markets. Thus, an analysis on the regional level will add value.

Moreover, the time period analysis shows major differences in the biotech portfolio in developed countries. The Sharpe ratio is 0.295% and -0.017% for the first 6 years and the last 6.5 years, respectively. This suggests that the biotech portfolio does not deliver consistent results over time, and the description of biotech as a cyclical sector seems to fit.

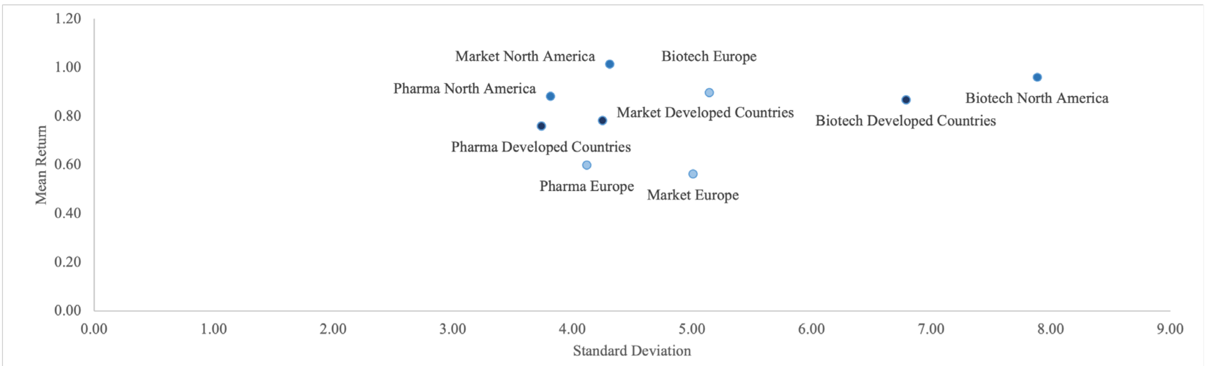
In sum, the essence is that the biotech portfolio in Europe and the pharma portfolio in North America show signs of outperformance. However, it is important to highlight that the Sharpe ratio considers both systematic and unsystematic risk factors in one measure. We need to study the systematic risk factors separately and examine alphas before we can conclude whether the returns have exceeded expectations.

Mean Returns and Standard Deviations

From the standard deviations, and the min and max returns, the biotech portfolios appear as high-risk investments and the pharma portfolios as low-risk investments. This seems reasonable as biotech is considered an emerging sector and pharma a mature sector, as discussed in earlier chapters. We observe that the biotech portfolio has the highest standard deviations and mean returns across regions. Nonetheless, investors are not fully compensated for their risk in developed countries and North America as the biotech portfolio does not deliver the highest Sharpe ratios in these regions. Thus, investors should be critical to investments in the biotech sector. We observe that the pharma portfolios have lower standard deviations and min and max returns than the market. This fits the description of pharma as a defensive sector, fluctuating less than the market.

Moreover, we observe that the last 6.5 years have been more volatile than the first 6 years for all portfolios, given the higher standard deviations, and min and max return. This is likely linked to the outbreak of Covid-19 in 2020, as well as the war in Ukraine and tighter monetary policy in 2022. For the two time periods, we note that the biotech portfolio has the highest standard deviations and that the pharma portfolio has less standard deviations than the market, as observed for the full time period. Figure 5.1 provides a visual summary of the standard deviations and mean returns. Here it becomes clear that the biotech portfolio in Europe has close to identical mean return as the biotech portfolio in North America despite having substantially lower standard deviation. We also see that the pharma portfolio in North America shows signs of outperformance.

Figure 5.1: Mean Return and Standard Error for Portfolios in Developed Countries, North America and Europe



5.1.2 Cumulative Returns

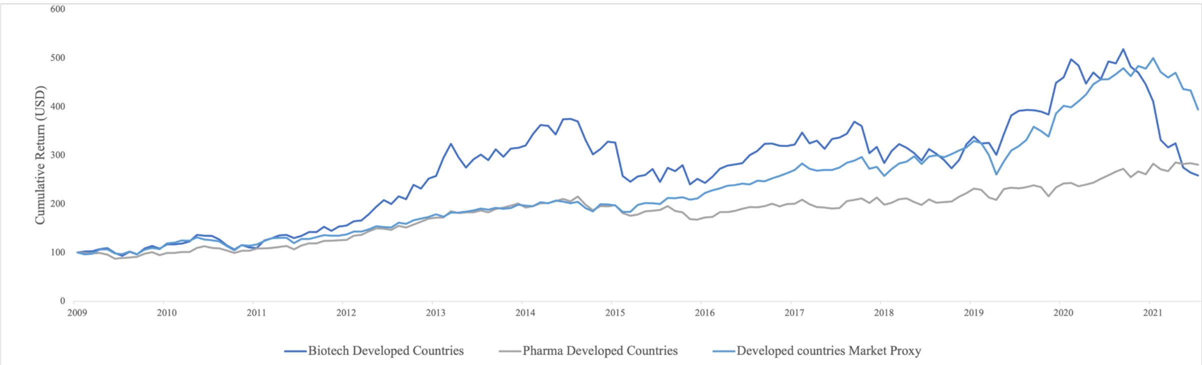
Portfolios in Developed Countries

Figure 5.2 shows the cumulative returns of a 100-dollar investment in the biotech portfolio, the pharma portfolio, and the market proxy in developed countries. The first finding is that the market proxy in developed countries delivers the highest absolute return of 294% since 2010. We observe that the market's cumulative return has fallen since 2020 but more interestingly we find that the biotech portfolio has fallen substantially more. The 100 dollars invested in the biotech portfolio in developed countries was 518 dollars in August 2021 and down to 263 dollars by June 2022. From this observation it seems unlikely that the biotech portfolio in developed countries has delivered positive abnormal returns. The observation aligns with the idea of biotech as a cyclical sector and it can also make us question the existence of a "biotech bubble" as there are several similarities to the prelude of the dot-com bubble. First, the low interest rates in recent years have increased the availability of capital. Second, the substantial increase in the number of listed biotech firms indicates that investors have been eager to invest in the sector. Third, the biotech portfolio exhibits high volatility, which was also a trait for tech firms during the dot-com bubble (Hayes, Adam, 2019).

Furthermore, the pharma portfolio delivered an absolute return well below the market. The 100 dollars invested in 2010 is only 280 dollars 12.5 years later. We observe that the pharma portfolio follows a relatively even line, which indicates that the sector has less volatility. This aligns with the standard deviations observed in the descriptive statistics.

In general, we see that the biotech portfolio reacts more strongly to market fluctuations than the pharma portfolio. Thus, we expect the market betas of biotech to be above or close to 1 and the market betas of pharma to be below 1. We observe that the two sectors are somehow opposites. Thus, an idea could be to combine the sectors in a mutual portfolio. A combined biotech and pharma portfolio would be more diversified but still exposed to the sector's technology trends. It would be a perfect fit for an investor that wants the action of the biotech sector in combination with the steadiness of pharma.

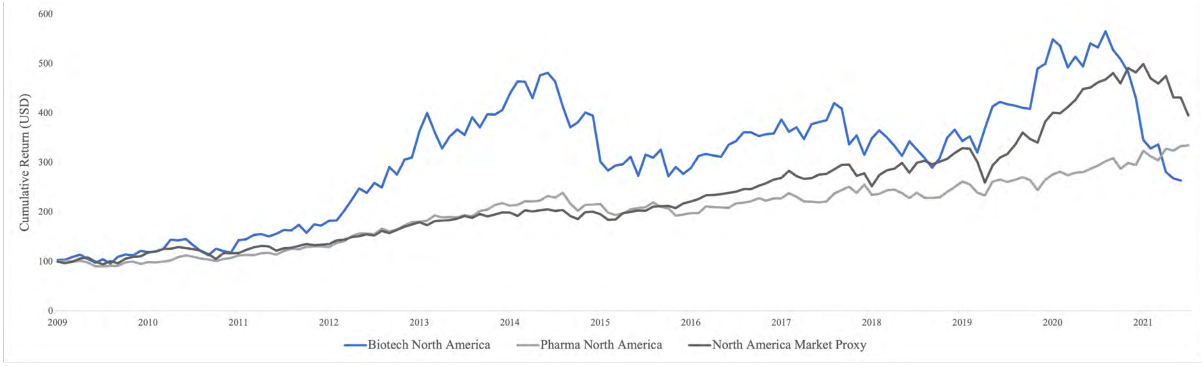
Figure 5.2: Cumulative Return of Portfolios in Developed Countries



Portfolios in North America

We also study the cumulative returns by continent. First, we observe that the market proxy in North America has delivered the highest cumulative returns of 295% during the sample period. This means that the market proxy delivers both the highest absolute returns and the highest risk-adjusted returns (Sharpe ratio) in North America. Furthermore, we observe that the biotech portfolio outperformed up until 2021, in which it suffered a massive fall in cumulative return. More specifically, the cumulative return fell 48% from January 2021 to June 2022. From this fall it seems unlikely that the biotech portfolio in North America has delivered positive abnormal returns on average in the full time period. The pharma portfolio has followed a more steady upward trend during the whole time period and does not seem to have suffered in recent years. The cumulative returns of pharma gives a neutral impression in terms of risk-adjusted returns. The cyclical and defensive characteristics are once again confirmed.

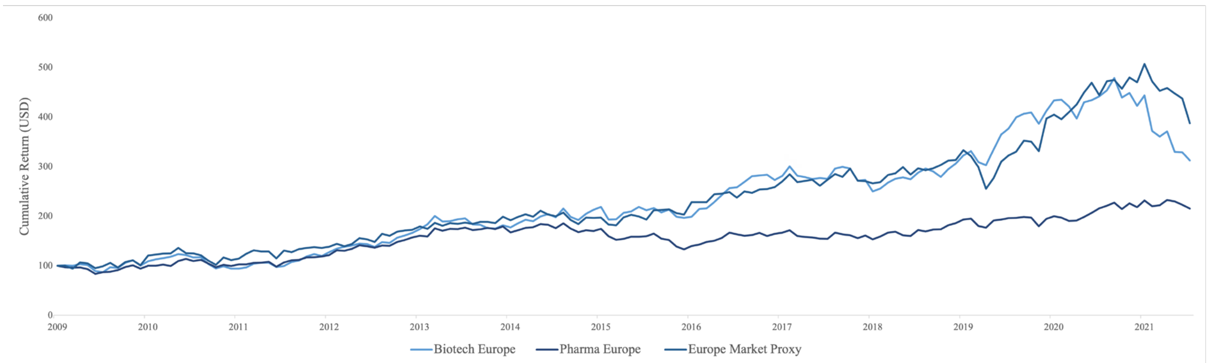
Figure 5.3: Cumulative Returns of Portfolios in North America



Portfolios in Europe

In Europe, we also note that the market proxy delivered the highest cumulative return of 287% during the sample period. We recall that the biotech portfolio in Europe had the highest risk-adjusted return from the descriptive statistics. Hence, the cumulative returns and risk-adjusted returns do not fully align for the biotech portfolio in Europe as it did for the market proxy in North America. We observe that the biotech portfolio in Europe has followed the market more closely and has fallen less since 2020 than the biotech portfolio in North America. The pharma portfolio in Europe exhibits similar trends as North America.

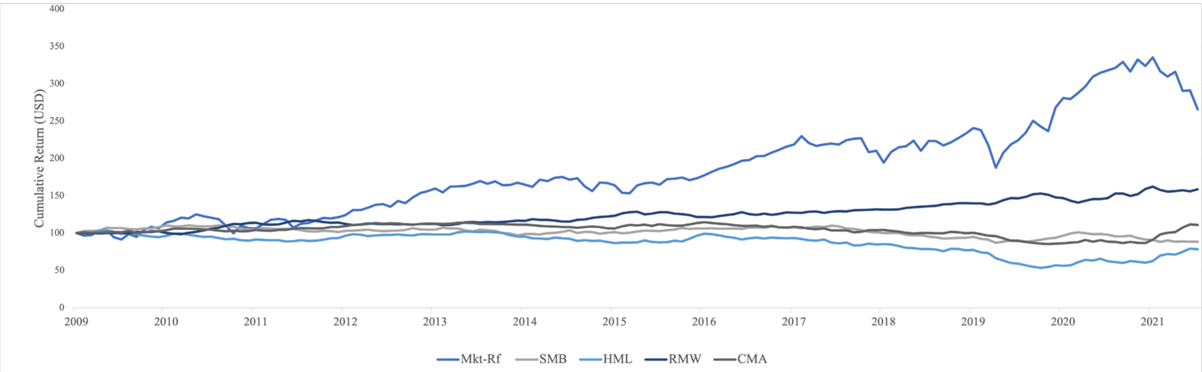
Figure 5.4: Cumulative Returns of Portfolios in Europe



Fama-French Factors in Developed Countries

We continue by exploring the historical performance of the Fama-French risk factors in chronological order. From Figure 5.5 we observe that the market factor has delivered the highest cumulative return of 165% during the sample period. This highlights that the power of the market factor has not diminished. We observe that the SMB factor has followed a negative trend during the sample period, which contradicts with the idea of a size premium. This observation aligns with the research of Asness et al. (2019) that found no evidence of a size premium among developed equity markets. However, we note that our sample period is shorter than the one studied by Fama and French and that the factors are exposed to macroeconomic cyclicity (Amenc et al., 2019). Furthermore, the HML factor has also followed a negative trend. Arnott et al. (2021) explain the underperformance by the weak book-to-value definition that does not adequately account for intangible assets and the plunge in valuations between value and growth stocks in recent years due to long-term low-interest rates. The CMA factor shows a mixed trend during the sample period. The factor has shown a slightly positive trend in recent years, which strengthens the idea of an investment premium. Lastly, the RMW factor exhibits a clear and positive absolute return. Thus, investing in profitable firms has been a sound investment strategy from 2010 to 2022.

Figure 5.5: Cumulative Return for Fama-French Factors in Developed Countries



Fama-French Factors in North America and Europe

We do a brief analysis of the historical performance of the Fama-French risk factors at a continent level as well. We note that the plot of the North American risk factors is fairly similar to the plot on the developed country level. Thus, we will focus on the differences in the European factors, which we see exhibited higher volatility compared to the developed factors. First, we notice that the return on the SMB factor is positive for Europe as opposed to North America and developed countries. This indicates that there has been a higher and positive size premium in Europe during the sample period. We also observe that the CMA factor is negative in Europe, which differs from the North American and developed countries' variant of the factor. This indicates that European investors have received excess returns for investments that are long in firms with aggressive investment strategies and short in firms with conservative investment strategies.

The study of the European and North American risk factors indicate that there can be advantages of conducting analyses on continent levels. This is also supported by the more recent studies of Fama and French (2017), which have shown that regional factor models outperform global factor models in explaining the cross-section of returns.

Figure 5.6: Cumulative Returns for Fama-French Factors in North America

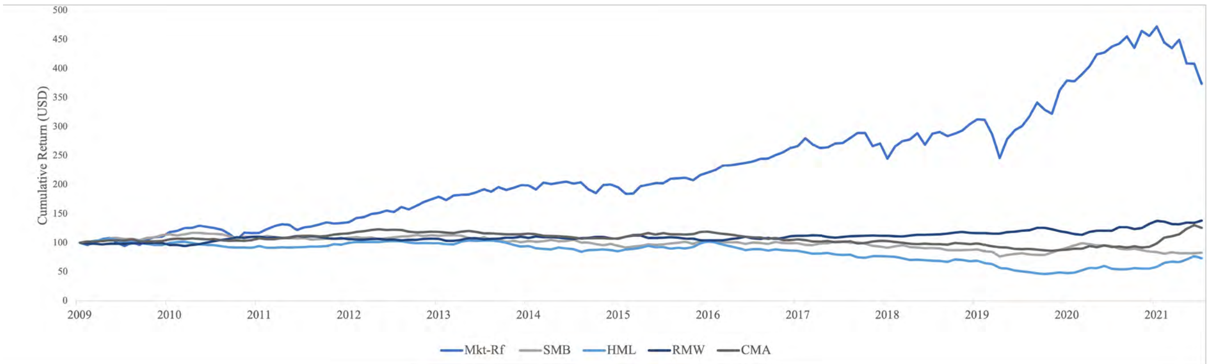
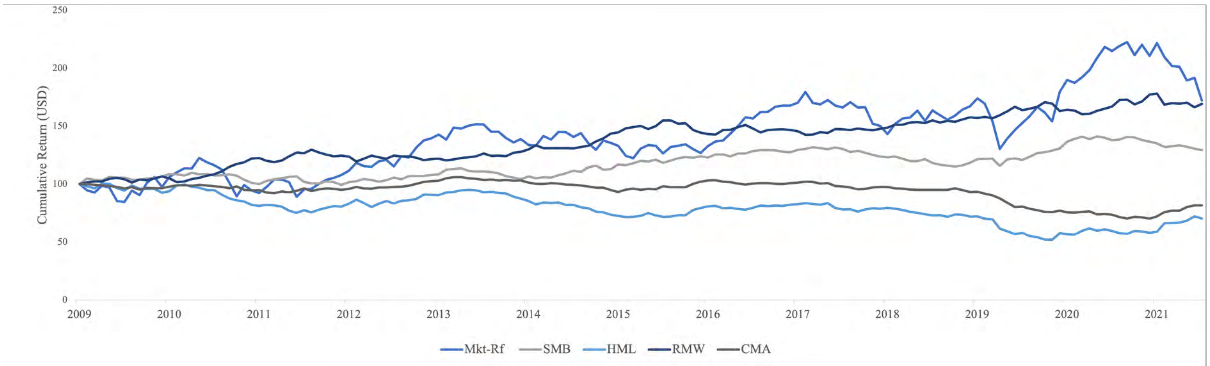


Figure 5.7: Cumulative Returns for Fama-French Factors in Europe



5.2 Return Percentiles

To gain a better understanding of the sector volatilities, we study the monthly portfolio returns at different percentiles. Overall, we observe that the 95th and 75th percentiles are higher for the biotech portfolio than the pharma portfolio. E.g., the 95% percentile in November 2015 was 0.49% and 0.30% for the biotech portfolio and pharma portfolio, respectively. The upper percentiles show that the 5% and 25% of the biotech returns lie above a higher value than the 5% and 25% of the pharma returns. This fits well with the observations of the cumulative returns, in which we saw that the biotech portfolio consistently delivered higher returns than the pharma portfolio. We observe that the biotech portfolio in North America exhibit more fluctuations in returns at the upper percentiles compared to Europe. This aligns with the descriptive statistics at continent level. There we saw that biotech portfolio in North America had approximately 50% higher standard deviation than the biotech portfolio in Europe. We also observe more extreme returns amongst the biotech portfolios compared to the pharma portfolios in recent years.

For the 5th and 25th percentiles, we naturally also observe more extreme values for the biotech portfolios. Thus, the poorest returns of biotech stocks lie below a lower value than the poorest returns of pharma stocks. Lastly, we can comment on the medians. Both sector portfolios exhibit medians above and below zero. We observe that the biotech portfolio has more extreme medians than the pharma portfolios. E.g., the median of the biotech portfolio and the pharma portfolio in developed countries was -0.18% and -0.11% in March 2020, respectively. In sum, the percentiles confirms the impressions from the standard deviations in the descriptitics, namely that the biotech sector is more volatile than the pharma sector.

Figure 5.8: Return Percentiles of the Biotech Portfolio in Developed Countries

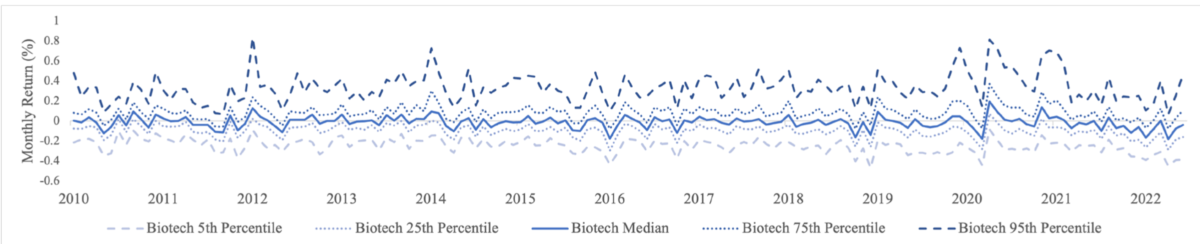


Figure 5.9: Return Percentiles of the Biotech Portfolio in North America

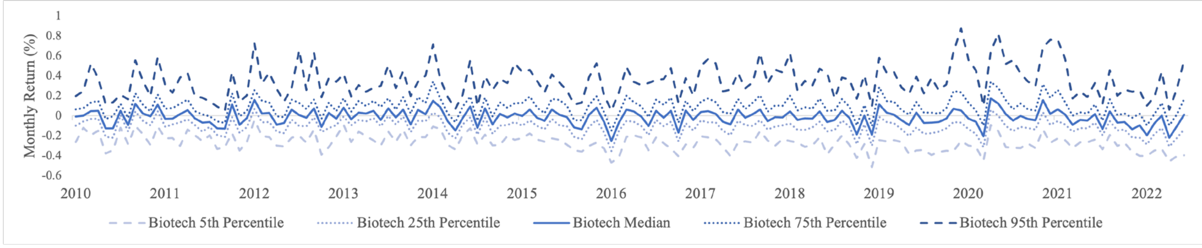


Figure 5.10: Return Percentiles of the Biotech Portfolio in Europe

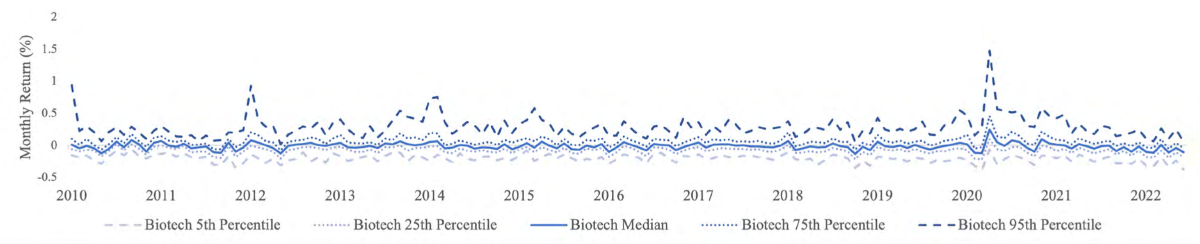


Figure 5.11: Return Percentiles of the Pharma Portfolio in Developed Countries

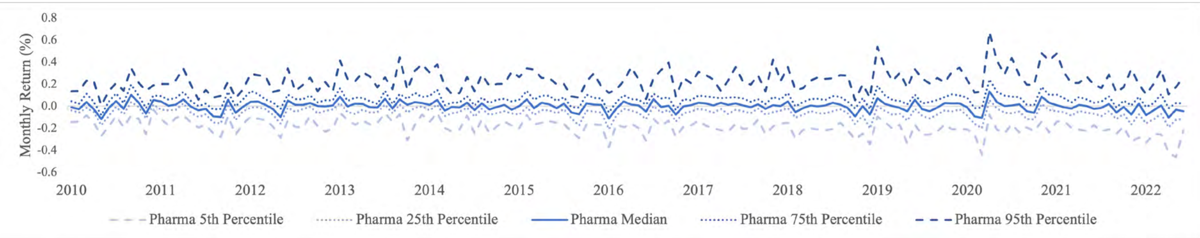


Figure 5.12: Return Percentiles of the Pharma Portfolio in North America

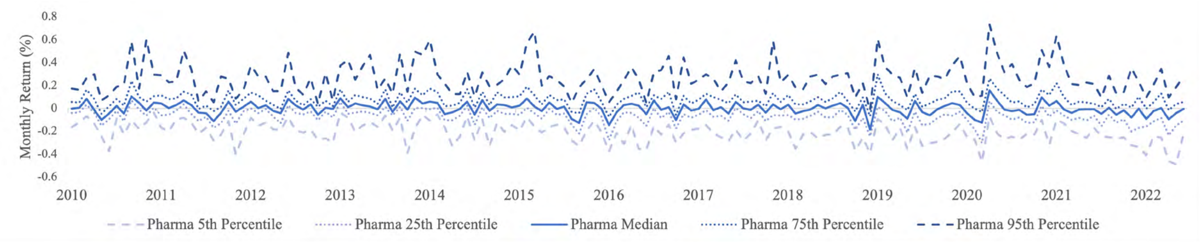
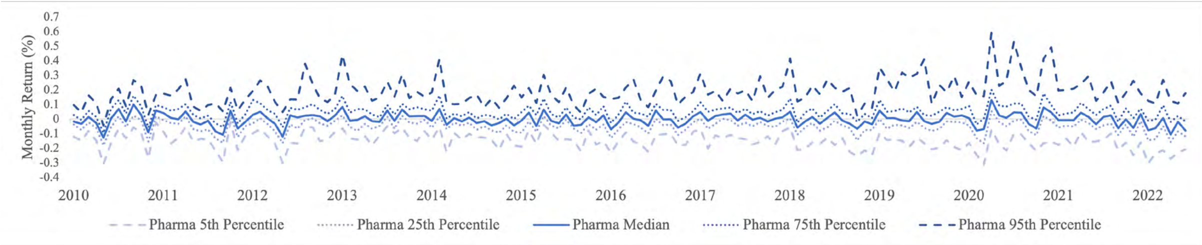


Figure 5.13: Return Percentiles of the Pharma Portfolio in Europe



5.3 Regression Results

In this section, we will present the regression results with the chosen main model, i.e., the Fama-French five-factor model. The analysis is centered around the portfolios in developed countries. We will also conduct analyses of continents, different time periods, and comparable indices to gain further insights. The objective is to answer whether the sector returns have exceeded what would be predicted by financial asset pricing models.

In answering this, we will apply the two main hypotheses that we presented at the beginning of the chapter. We will test two-sided null hypotheses against the alternative hypotheses as we accept that the estimated values can be significantly greater and significantly less than the sample mean. More specifically, we will test whether the chosen model presents significant alphas, i.e., significant abnormal returns, with the Fama-French factors. Note that we will not consider the model's ability to describe stocks returns by constructing our own factors like one can do with Fama McBeth regressions (Fama and MacBeth, 1973). We will apply a 5% significance level as recommended by Andrade (2019). A rejection of the null hypothesis will suggest that the returns of the tested portfolio have exceeded the expectations of the applied financial asset pricing model.

We will test long-only portfolios, in which the dependent variable is the portfolio return in excess of the risk-free rate. The regression coefficients will show us the loadings (also referred to as betas) of the different systematic risk factors. Hence, they will display the attributes of the stocks in the portfolios.

5.3.1 Main Portfolios

Table 5.2 presents the average alphas and factor betas for the sector portfolios for stocks in developed countries. First, we observe that none of the alphas are significant. Hence, we cannot reject any of our null hypotheses, and we cannot conclude that the returns of biotech or pharma stocks in developed countries have exceeded the returns predicted by the Fama-French five-factor model.

Table 5.2: Sector Portfolios in Developed Countries

	Dependent variable: $R_{rst}^{V} - R_{ft}$	
	Biotech	Pharma
α	0.518	0.017
	(0.337)	(0.213)
β_{MKT}	0.969***	0.712***
	(0.079)	(0.050)
β_{SMB}	0.888***	-0.279*
	(0.233)	(0.147)
β_{HML}	-1.157***	-0.593***
	(0.226)	(0.143)
β_{RMW}	-1.497***	0.024
	(0.312)	(0.197)
β_{CMA}	-0.342	0.868***
	(0.347)	(0.219)
Observations	150	150
R^2	0.690	0.594
Adjusted R^2	0.680	0.579
Note:	*p<0.1; **p<0.05; ***p<0.01	

The table provides the regression results for the biotech portfolio and the pharma portfolio in developed countries, using monthly return data from January 2010 to June 2022. We apply the generalized formula $R_{rst}^{V} - R_{ft}$ as the dependent variable, in which r corresponds to Developed Countries, s corresponds to the sectors, V denotes that the portfolio is value-weighted, and R_{ft} denotes the risk-free rate. The alpha is the constant term and represents the monthly abnormal return in percent. The betas capture the loadings to the systematic risk factors of the Fama-French five-factor model. MKT is the value-weighted market return minus the risk-free rate. SMB (Small Minus Big) captures the portfolio's exposure to small market cap stocks. HML (High Minus Low) captures the portfolio's exposure to high book-to-market stocks. RMW (Robust Minus Weak) captures the exposure to firms with robust profitability. CMA (Conservative Minus Aggressive) captures the exposure to a conservative investment strategy.

Second, we observe that all portfolios show a significantly positive market beta. The biotech portfolio fluctuates almost identically to the market in developed countries as the average monthly market beta is 0.969[11]. The pharma portfolio is less sensitive to the market given the beta of 0.712. These results fit the intuitions formed by the descriptive statistics, namely that biotech stocks and pharma stocks have cyclical and defensive characteristics, respectively.

Third, we observe that the biotech portfolio tilts toward small-cap firms given the significant size beta of 0.888. This is close to 1, which implies that the biotech portfolio almost moves identically with the size factor. The pharma portfolio does not exhibit a significant size beta. Thus, we cannot conclude that this portfolio is exposed to the size premium at the 5% significance level. The loadings to the size beta seem reasonable if we consider the industry composition discussed in Chapter 3. There we saw that the biotech sector was dominated by small-, nano- and micro-cap firms, while the pharma sector had a more even distribution. The difference in firm size can be explained by the fact that biotech is an emerging sector with many small and newly established firms, whereas pharma is a mature sector in which industry leaders have had time to be formed (Bodie et al., 2020).

Fourth, the value beta is significantly negative for all the sector portfolios, which indicates that the majority of the firms are low book-to-market stocks. This is in line with the findings of Dong and Guo (2013) in the health care service sector. A possible explanation is that health care stocks have assets in clinical development phases or patent rights that may not be reflected on the balance sheet. We observe that the value beta is more extreme for the biotech portfolio than the pharma portfolio with loadings of -1.157 and -0.593, respectively. This seems reasonable given that the biotech sector has a higher R&D intensity and the pharma sector also has drug manufacturing to lean on (Burns, 2020).

The last two factors show varying significance across the sectors. We observe that the biotech portfolio is oriented toward firms with weak profitability given the significant profitability beta of -1.497. This implies a negative correlation with the profitability factor, which can be related to the fact that most biotech firms have high R&D costs and do not have product sales in the market. The profitability beta is insignificant for the pharma portfolio. Furthermore, the significant investment beta of 0.868 for the pharma portfolio indicates that the majority of the firms in this sector have a conservative investment strategy. This seems reasonable as pharma firms typically have high-margin

[11]A beta of 1 signifies that the portfolio moves identically with the risk factor. A beta of -1 signifies that the portfolio moves in the opposite direction of the risk factor.

drugs in production and are less dependent on new investments. The investment beta is insignificant for the biotech portfolio.

As with all regression analyses, it is important to discuss the model fit. We view the adjusted R-squared as this number is adjusted for added explanatory variables (Wooldridge, 2012). The market, size, value and profitability betas explain 68.0% of the biotech portfolio return. The market, size, value and investment betas explain 57.9% of the pharma portfolio return. As the explanatory powers are not 100%, some parts of the return may be random or due to unobserved factors. The unobserved factors can be both systematic and unsystematic of nature. We will test for other systematic risk factors in the robustness analysis. It is likely that parts of the unobserved risk factors are unsystematic as we study sector portfolios that are not fully diversified. These unsystematic factors will be further discussed in Chapter 6.

To summarize, we can view the monthly hypothetical return contributions [12] of the biotech portfolio and pharma portfolio in Table 5.3 and 5.4, respectively. Note that we cannot rely on the betas that are insignificant. Nonetheless, we include the hypothetical return contribution as part of an illustrative example as done by Isreal and Ross (2017). The average monthly excess return above the risk-free rate is 0.827% for the biotech portfolio and 0.721% for the pharma portfolio in developed countries during the study period. We note that the market betas account for the majority of the return contribution on average, with 0.72% for the biotech portfolio and 0.53% for the pharma portfolio. We also note that the profitability beta reduces the excess return of the biotech portfolio on average by -0.473%. The significant betas lead us to the conclusion that an investor that wants exposure to market volatility and small low-book-to-market firms with weak profitability should invest in a portfolio of biotech firms. While an investor that wants exposure to less market volatility and large low book-to-market firms with a conservative investment strategy should invest in a portfolio of pharma firms.

[12] The hypothetical return contributions are calculated by multiplying the estimated factor betas with their corresponding average monthly risk premium between January 2010 and June 2022.

Table 5.3: Hypothetical Return Contribution by Factor Beta for the Biotech portfolio

	Estimated Factor Beta		Risk Premium		Return Contribution
α	0.518% *(0.337)*			=	0.518%
β_{MKT}	0.969*** *(0.079)*	x	0.742%	=	0.719%
β_{SMB}	0.888*** *(0.233)*	x	-0.072%	=	-0.064%
β_{HML}	-1.157 *(0.226)*	x	-0.133%	=	0.154%
β_{RMW}	-1.497*** *(0.312)*	x	0.316%	=	-0.473%
β_{CMA}	-0.342 *(0.347)*	x	0.080%	=	-0.027%
Adjusted R^2	0.680		**Excess Return**	=	**0.827%**

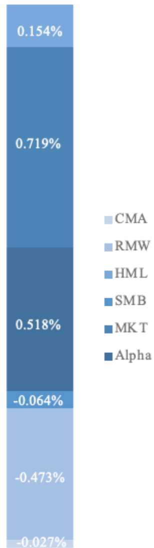
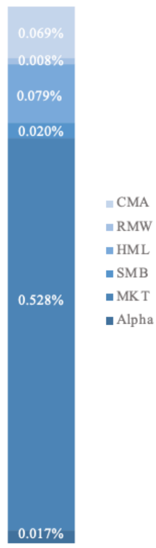


Table 5.4: Hypothetical Return Contribution by Factor Beta for the Pharma portfolio

	Estimated Factor Beta		Risk Premium		Return Contribution
α	0.017% *(0.213)*				0.017%
β_{MKT}	0.712*** *(0.050)*	x	0.742%	=	0.528%
β_{SMB}	-0.279* *(0.147)*	x	-0.072%	=	0.020%
β_{HML}	-0.593*** *(0.143)*	x	-0.133%	=	0.079%
β_{RMW}	0.024 *(0.197)*	x	0.316%	=	0.008%
β_{CMA}	0.868 *(0.219)*	x	0.080%	=	0.069%
Adjusted R^2	0.579		**Excess Return**	=	**0.721%**



5.3.2 Continent Portfolios

Now that we have analyzed the portfolios for developed countries as a whole, we wish to analyze the sectors in Europe and North America separately. There are several reasons why an analysis on a continent level adds value. First, we saw that the continent sector portfolios viewed varying results in the descriptive statistics, which makes us wonder whether there are differences in alphas and factor exposures as well. Second, investment managers often have restrictions in terms of exposure to certain factors and geographics as emphasized by the expert group in Dahlquist and Ødegaard (2018). E.g., the geographical composition of the Government Pension Fund of Norway has been tilted towards European investments since its inception due to requirements from the Norwegian Ministry of Finance (Norges Bank Investment Management, 2019). Third, Fama and French (2017) have shown that regional factor models outperform global factor models in explaining the cross-section of returns. This aligns with the differences in the cumulative returns of the continent-specific Fama-French risk factors. Note that we will focus on discussing the differences between the regression analysis on the developed country level and the continent level, rather than restate common findings. The regression results are presented in Table 5.5

First, we observe that the alpha for the biotech portfolio in Europe is significant at a 5% level. This indicates that the sector has delivered an average monthly abnormal return of 0.407%. Hence, we can reject the first null hypothesis in favor of the alternative hypothesis, *The biotech portfolio* ***does*** *deliver significant abnormal returns.* The results imply that the biotech portfolio in North America lowers the alpha of the biotech portfolio in developed countries. A review of the Z-scores confirms this. The Z-score for the biotech portfolio is 1.537 in developed countries and 0.320 in North America, whereas the latter value is far away from the critical value of 1.96[13]. We observe that none of the other regional sector portfolios exhibit significant alphas. This is not consistent with the findings of Thakor et al. (2017) and Koijen et al. (2016) who both found a significant alpha for pharma stocks in the U.S. However, the research period of Thakor et al. (2017) was from 1930 to 2015, while the research period of Koijen et al. (2016) was from 1960 to 2010. Hence, our results imply that positive abnormal returns are not present amongst pharma firms in recent

[13]We calculate the Z-score by dividing the estimated coefficient on standard error. The critical value of 1.96 is retrieved from a Z-score table for a two-sided test at a 5% significance level with an infinite number of observations (n>100).

Table 5.5: Sector Portfolios in North America and Europe

	Dependent variable: $R^V_{rst} - R_{ft}$			
	North America		Europe	
	Biotech	Pharma	Biotech	Pharma
α	0.131	-0.069	0.407**	0.191
	(0.410)	(0.222)	(0.205)	(0.219)
β_{MKT}	0.893***	0.677***	0.965***	0.755***
	(0.099)	(0.053)	(0.051)	(0.050)
β_{SMB}	1.009***	-0.197*	0.291**	-0.355***
	(0.208)	(0.113)	(0.130)	(0.128)
β_{HML}	-1.241***	-0.629***	-1.118***	-0.633***
	(0.212)	(0.115)	(0.161)	(0.158)
β_{RMW}	-0.953***	-0.178	-0.716***	0.056
	(0.277)	(0.150)	(0.219)	(0.215)
β_{CMA}	0.213	0.994***	0.248	0.627***
	(0.323)	(0.175)	(0.228)	(0.225)
Observations	150	150	150	150
R^2	0.655	0.568	0.757	0.634
Adjusted R^2	0.643	0.553	0.749	0.622
Note:		*p<0.1; **p<0.05; ***p<0.01		

The table provides the regression results for the biotech portfolio and the pharma portfolio, using monthly return data from January 2010 to June 2022. We apply the generalized formula $R^V_{rst} - R_{ft}$ as the dependent variable, in which r corresponds to North America and Europe, s corresponds to the sectors, V denotes that the portfolio is value-weighted, and R_{ft} denotes the risk-free rate. The alpha is the constant term and represents the monthly abnormal return in percent. The betas capture the loadings to the systematic risk factors of the Fama-French five-factor model. MKT is the value-weighted market return minus the risk-free rate. SMB (Small Minus Big) captures the portfolio's exposure to small market cap stocks. HML (High Minus Low) captures the portfolio's exposure to high book-to-market stocks. RMW (Robust Minus Weak) captures the exposure to firms with robust profitability. CMA (Conservative Minus Aggressive) captures the exposure to a conservative investment strategy.

years. In addition, Thakor et al. (2017) and Koijen et al. (2016) applied the CAPM and Fama-French three-factor model, respectively. As a result, the abnormal returns found for pharma stocks may be explained by the risk factors included in the Fama-French five-factor model.

Next, we observe that biotech and pharma stocks in North America fluctuate less than their respective markets with market betas of 0.893 and 0.677, respectively. The respective market betas in Europe are a bit higher but still less than 1. A possible explanation could be that the North American firms in the pharma and biotech sector have a more stable revenue stream and dividend policy than the European ones. It could also be related to

European regulations, which are known for being more strict than American (Golec and Vernon, 2009).

Furthermore, we observe a positive significant size beta of 1.009 for the North American biotech portfolio, which signifies that the portfolio's size exposure is almost identical to the size factor. The exposure is almost three times as high as the European one of 0.291. In other words, the biotech portfolio in North America is more tilted toward small-cap stocks. This seems reasonable if we recall the industry composition from Chapter 3. There we observed that there were three times as many biotech firms in North America compared to Europe. The negative size beta for the pharma portfolio is only significant at a 5% level for the European portfolio. This suggests that the European pharma portfolio is tilted towards large firms. This is also consistent with the findings from the market cap classification in the industry composition in Chapter 3, where we observed a relatively high proportion of mega- and large-cap firms in Europe.

Moreover, we observe negative value betas for all the sector portfolios. This is in accordance with the observations of the portfolios for developed countries and the findings of Dong and Guo (2013). This is the opposite of other industries where high book-to-market stocks are preferred. Again, we observe that the biotech portfolios have more extreme negative value betas. Dong and Guo (2013) argues that the number of patents and the lock-up periods of patents are more valued than what appears on the firm's book value, which is the cause of the negative value beta. The profitability beta and investment beta also show similar significant results as viewed for stocks in developed countries. That is, the biotech portfolios consist of stocks with weak profitability and the pharma portfolios consist of stocks with conservative investment strategies.

Lastly, we review the adjusted R-squared. We observe that the European portfolios exhibit the highest explanatory powers. This indicates that the chosen model fits the European portfolios better. We have the same sample size, i.e., return observations for both continents. However, there are more firms contributing to the return in North America than in Europe, as reviewed in the industry composition. In addition, we observed that the growth in the number of firms was higher in North America. We know that firms tend to be highly volatile in the period following an initial public offering (IPO) (Lowery et al., 2010). Thus, it seems reasonable that the portfolios in North America have a lower explanatory power as this indicates higher variation in returns.

To sum up, the European biotech portfolio exhibited a significantly positive alpha, and we can reject our first null hypothesis. The betas indicate similar risk exposures on a continent level as developed countries as a whole. The most noticeable difference is the size beta of the biotech portfolio, which is three times as high in North America than in Europe. This suggests that North America is a preferred listing location for young biotech firms.

5.3.3 Time Period Portfolios

Now that we have analyzed the continent differences, we would like to study the results over different time periods. We have chosen to split the analyzed period in two: the first 6 years and the last 6.5 years. The time period analysis adds value as it models the average returns from different starting points so that we can capture trends. As we study these portfolios, it is worth noting that the number of observations is nearly halved (n=72, n=78). However, this should still be enough observations for adequate statistical power according to Wooldridge (2012). Table 5.6 presents the regression results for the time period portfolios.

The first striking finding is that the alpha for the biotech portfolio in developed countries is significantly positive for the first 6 years at a 10% level. The Z-score is 1.939, which is close to the critical value of 1.96 for the 5% significance level. Nonetheless, we cannot reject our first null hypothesis as we apply the 5% significance level. We observe that none of the other time period portfolios exhibit significant alphas. In sum, we cannot conclude that biotech and pharma stocks have exceeded the returns of the Fama-French five-factor model during these time periods.

We observe that the biotech portfolio fluctuated slightly more than the market in the first 6 years given the beta of 1.024 and slightly less during the last 6.5 years given the beta of 0.908. The pharma portfolio shows less sensitivity to the market in both periods with a beta far below 1. An interesting observation is that the pharma portfolio was more exposed to the market in the second time period. This makes us question the sector's defensive characteristics as the second time period included the uncertainties of Covid-19.

Next, we observe that the significantly positive size betas for the biotech portfolio are

Table 5.6: Time Period Portfolios in Developed Countries

	Dependent variable: $R^V_{rst} - R_{ft}$			
	First 6 years		Last 6.5 years	
	Biotech	Pharma	Biotech	Pharma
α	1.045*	0.357	-0.118	-0.249
	(0.539)	(0.316)	(0.430)	(0.297))
β_{MKT}	1.024***	0.681***	0.908***	0.784***
	(0.141)	(0.082)	(0.109)	(0.075)
β_{SMB}	0.860**	-0.372*	0.844***	-0.238
	(0.376)	(0.220)	(0.310)	(0.214)
β_{HML}	-1.567***	-0.456*	-0.844***	-0.800***
	(0.414)	(0.242)	(0.278)	(0.192)
β_{RMW}	-1.252**	0.110	-1.478***	-0.158
	(0.608)	(0.356)	(0.379)	(0.262)
β_{CMA}	0.550	0.184	-0.889**	1.263***
	(0.643)	(0.377)	(0.422)	(0.292)
Observations	72	72	78	78
R^2	0.621	0.609	0.766	0.618
Adjusted R^2	0.592	0.579	0.750	0.591

Note: *p<0.1; **p<0.05; ***p<0.01

The table provides the regression results for the biotech portfolio and the pharma portfolio for stocks in developed countries, using monthly return data from January 2010 to June 2022. We apply the generalized formula $R^V_{rst} - R_{ft}$ as the dependent variable, in which r corresponds to Developed Countries, s corresponds to the sectors, V denotes that the portfolio is value-weighted, and R_{ft} denotes the risk-free rate. The alpha is the constant term and represents the monthly abnormal return in percent. The betas capture the loadings to the systematic risk factors of the Fama-French five-factor model. MKT is the value-weighted market return minus the risk-free rate. SMB (Small Minus Big) captures the portfolio's exposure to small market cap stocks. HML (High Minus Low) captures the portfolio's exposure to high book-to-market stocks. RMW (Robust Minus Weak) captures the exposure to firms with robust profitability. CMA (Conservative Minus Aggressive) captures the exposure to a conservative investment strategy.

similar in the first 6 years and the last 6.5 years. The size beta is not significant for the pharma portfolio in any of the time periods. In other words, the size beta shows consistency across shorter time periods and also aligns with what was observed for the full time period.

Moreover, we observe that the value beta for the biotech portfolio is significantly more negative in the first 6 years compared to the last 6.5 years. This indicates that the first period consists of more low book-to-market firms than the second period. The value beta for pharma is significantly negative only for the second time period. The profitability beta for the biotech portfolio is negative in both time periods with similar coefficients as observed on the developed country level. We observe a significantly positive investment beta for the pharma portfolio in the second time period, which indicates that the portfolio consisted of more firms with conservative investment strategies during this time period. In sum, the time period portfolios show that there are some changes in coefficients, suggesting that firm or sector characteristics have changed over time.

Lastly, we observe that the adjusted R-squared is overall higher for the shorter time periods than for the full time period. This seems reasonable as the full time period exhibited higher variation from the cumulative return graphs. The higher explanatory powers of the shorter time periods indicate that we can trust the relationships between the significant variables more than the total time period. Nonetheless, we should be skeptical to use these estimates as forecasts for the following period.

5.3.4 Sector Indices

Our thesis studies portfolios that include all listed stocks in the biotech and pharma sectors. The purpose has been to detect sector-specific risk factor exposures and whether the sector returns have exceeded what would be predicted by the Fama-French five-factor model. This adds value as we know that active investment managers sometimes follow sector-specific strategies. However, we know that certain players rather follow a passive strategy. Thus, we wish to do the same analyses on sector indices in North America as this is an example of an accessible investment option. We use the S&P 500 Pharmaceutical and S&P 500 Biotechnology sector indices, which are both value-weighted. Table 5.7 presents the regression results for the S&P 500 Biotechnology and S&P 500 Pharmaceuticals.

We begin by observing that none of the indices report a significant alpha, which aligns with the results for North America when studying all stocks in the sectors. The significant market beta for the S&P 500 Biotechnology is lower than the one observed for our biotech portfolio. It seems reasonable that the index is less sensitive to the market as the smallest stocks are excluded. The same reasoning goes for the insignificant size beta for the S&P 500 Biotechnology. We observe a significantly negative size beta for S&P 500 Pharmaceuticals, which suggests that the index is tilted towards big caps. This differs from the insignificant size beta observed for our North American pharma portfolio and suggests that there

Table 5.7: S&P 500 Sector Indices in the United States

	Dependent variable: $R_{bt}^V - R_{ft}$	
	S&P 500 Biotechnology	S&P 500 Pharmaceutical
α	0.271	-0.136
	(0.374)	(0.225)
β_{MKT}	0.743***	0.675***
	(0.090)	(0.054)
β_{SMB}	-0.099	-0.315***
	(0.190)	(0.114)
β_{HML}	-0.818***	-0.562***
	(0.194)	(0.116)
β_{RMW}	-0.443*	-0.008
	(0.253)	(0.152)
β_{CMA}	0.933***	1.001***
	(0.295)	(0.177)
Observations	150	150
R^2	0.389	0.553
Adjusted R^2	0.367	0.538
Note:		*p<0.1; **p<0.05; ***p<0.01

The table provides the regression results for the S&P 500 Biotechnology and S&P 500 Pharmaceutical indices for stocks in the US, using monthly return data from January 2010 to June 2022. We apply the generalized formula $R_{bt}^V - R_{ft}$ as the dependent variable, in which b corresponds to the indices, V denotes that they are value-weighted, and R_{ft} denotes the risk-free rate. The alpha is the constant term and represents the monthly abnormal return in percent. The betas capture the loadings to the systematic risk factors of the Fama-French five-factor model. MKT is the value-weighted market return minus the risk-free rate. SMB (Small Minus Big) captures the portfolio's exposure to small market cap stocks. HML (High Minus Low) captures the portfolio's exposure to high book-to-market stocks. RMW (Robust Minus Weak) captures the exposure to firms with robust profitability. CMA (Conservative Minus Aggressive) captures the exposure to a conservative investment strategy.

are enough small firms in our portfolio to make the size beta insignificant. The value betas are significantly negative for both of the S&P 500 indices. This strengthens our conception that biotech and pharma stocks are characterized as low book-to-market stocks. However, we observe that the value coefficients are slightly higher for the sector indices. This suggests that small biotech and pharma firms have lower book-to-market values.

Next, we observe insignificant profitability betas for both indices at a 5% level. This contradicts the biotech portfolio in developed countries and suggests that small biotech firms contributed to the significantly negative profitability beta. Finally, both indices are tilted towards firms with conservative investment strategies with almost identical betas of 0.933 and 1.001. This is inconsistent with the observations of our full sector portfolios, in which only the pharma portfolio exhibited a significantly positive investment beta. This suggests that the top 500 largest firms in both sectors have a more low-risk investment strategy.

We observe that the adjusted R-squared is higher for S&P 500 Pharmaceuticals than S&P 500 Biotechnology. This differs from prior regression results, in which the biotech portfolio has had higher explanatory power than the pharma portfolio. It is also worth noting that the adjusted R-squared is lower for the indices compared to the full sector portfolios. This indicates that the Fama-French five-factor model explains a higher percentage of variation in our portfolio returns compared to the returns of the indices. A possible explanation is that we have included stocks at all market cap levels, while the indices are restricted to the top 500. Fama-French also uses stocks at all market cap levels when constructing the factors (Fama and French, 1993).

5.4 Robustness Analysis

5.4.1 Alternative Factor Models

Another method to evaluate the robustness of the results is to perform several alternative factor regressions. For the biotech and pharma portfolio in developed countries, we apply the CAPM, Fama-French three-factor model, Carhart four-factor model, Fama-French five-factor model, Fama-French five-factor model plus momentum and a seven-factor model. We will use the correlations coefficients[14] of the Fama-French risk factors presented in Table 5.8 to explain some of the results. A correlation of 1 indicates a strong positive relationship, a correlation of -1 indicates a strong negative relationship, and a correlation of 0 indicates no relationship between the coefficients.

Biotech Portfolio

The regression results for the biotech portfolio in developed countries with multi-factor models are presented in Table 5.9. First, we observe that none of the factor regressions deliver significantly positive alphas for the biotech portfolio in developed countries. This strengthens the finding from our main analysis, namely that the biotech portfolio in developed countries does not deliver positive abnormal returns.

[14] Correlation coefficients for the Fama-French risk factors for North America and Europe can be found in appendix A2.1

Table 5.8: Pearson Correlation Coefficients for Fama-French Risk Factors in Developed Countries

	Mkt	SMB	HML	RMW	CMA	MOM	BAB	QMJ
Developed countries								
Mkt	1.000							
SMB	0.107	1.000						
HML	0.051	0.114	1.000					
RMW	-0.197	-0.334	-0.522	1.000				
CMA	-0.180	-0.030	0.763	-0.271	1.000			
MOM	-0.272	-0.100	-0.505	0.343	-0.179	1.000		
BAB	-0.100	0.124	-0.100	0.175	0.030	0.415	1.000	
QMJ	-0.648	-0.398	-0.182	0.682	0.120	0.315	0.192	1.000

We observe significant positive market and size betas across all models. These betas decrease as more factors are added, which suggests that the added factors in the more extensive models explain some of the exposure to the market and size factor in the simpler models. The decrease in betas also aligns with the negative correlation coefficients that market and size exhibit towards RMW, CMA and MOM. Furthermore, we observe a significantly negative value beta across all models. This strengthens our conception that the biotech portfolio is tilted towards low book-to-market stocks.

When the momentum factor is added to the three-factor and five-factor models, the coefficients remain the same in terms of significance. This is reasonable as the momentum factor is not statistically significant for either of the models. However, several of the betas increase or decrease slightly. A possible explanation is that the momentum factor is correlating with some of the other factors, which Fama and French (2015) have argued might be an issue when including this factor. Momentum correlates the most with HML by -0.505, which can explain the less negative HML from the five-factor model to the five-factor model with momentum. Furthermore, it seems reasonable that the momentum factor is insignificant for the biotech portfolio. This is because the sector is highly volatile, and the winners in one period might be the losers in the next period. Therefore, we can question whether there exists a short-term reversal effect instead. That is, stocks with relatively low (high) returns over the past month earn a positive (negative) abnormal return in the following month (Swade et al., 2022). The equally-weighted portfolio can help us investigate this further.

Moreover, the betas of CMA, BAB and QMJ are not significant for either of the multi-

Table 5.9: Biotech Portfolio in Developed Countries with Alternative Factor Models

	Dependent variable: $R^V_{rst} - R_{ft}$				
	FF3	Carhart	FF5	FF5 + Mom	Seven-factor
α	0.006	0.003	0.518	0.480	0.604
	(0.345)	(0.357)	(0.337)	(0.344)	(0.380)
β_{MKT}	1.060***	1.061***	0.969***	0.978***	0.935***
	(0.080)	(0.084)	(0.079)	(0.081)	(0.114)
β_{SMB}	1.272***	1.272***	0.888***	0.884***	0.872***
	(0.237)	(0.238)	(0.233)	(0.233)	(0.252)
β_{HML}	-0.954***	-0.951***	-1.157***	-1.081***	-1.155***
	(0.134)	(0.156)	(0.226)	(0.260)	(0.230)
β_{MOM}		0.004		0.089	
		(0.153)		(0.149)	
β_{RMW}			-1.497***	-1.498***	-1.342***
			(0.312)	(0.313)	(0.461)
β_{CMA}			-0.342	-0.407	-0.303
			(0.347)	(0.364)	(0.357)
β_{BAB}					-0.048
					(0.189)
β_{QMJ}					-0.148
					(0.357)
Observations	150	150	150	150	150
R^2	0.635	0.635	0.690	0.691	0.691
Adjusted R^2	0.628	0.625	0.680	0.678	0.676
Note:					*p<0.1; **p<0.05; ***p<0.01

The table provides the regression results for the biotech portfolio in developed countries with multiple factor models, using monthly return data from January 2010 to June 2022. We apply the generalized formula $R^V_{rst} - R_{ft}$ as the dependent variable, in which r corresponds to Developed Countries, s corresponds to Biotech, V denotes that the portfolio is value-weighted, and R_{ft} denotes the risk-free rate. The alpha is the constant term and represents the monthly abnormal return in percent. The betas capture the loadings to the systematic risk factors. MKT is the value-weighted market return minus the risk-free rate. SMB (Small Minus Big) captures the portfolio's exposure to small market cap stocks. HML (High Minus Low) captures the portfolio's exposure to high book-to-market stocks. RMW (Robust Minus Weak) captures the exposure to firms with robust profitability. CMA (Conservative Minus Aggressive) captures the exposure to a conservative investment strategy. BAB (Betting Against Beta) captures the exposure to lower beta assets. QMJ (Quality Minus Junk) captures the exposure to quality stocks.

factor models. The insignificant CMA beta aligns with the observations in the main analysis. We cannot conclude that the biotech portfolio is exposed to the betting against the beta factor and the quality factor. When looking at the seven-factor model, we observe that most betas decrease in magnitude and significance compared to the Fama-French five-factor model. E.g., the size beta in the Fama-French five-factor model decrease from 0.888 to 0.872 in magnitude, and 3.81 to 3.46 in Z-score, compared to the seven-factor model. This can be because BAB and QMJ correlate with the other factors.

Lastly, we observe that the adjusted R-squared is the largest for the Fama-French five-factor model without momentum. This suggests that the explanatory power of an asset pricing model is not necessarily improved by adding more factors. It also confirms that our choice of the main model is optimal.

Pharma Portfolio

We continue by examining the alternative factor models for the pharma stocks. As presented in Table 5.10, none of the models show significant alphas. This strengthens the finding from our main analysis, namely that the pharma portfolio in developed countries does not deliver positive abnormal returns. It contradicts the findings of Koijen et al. (2016) and Thakor et al. (2017), who found significant alphas for pharma stocks. The positively significant market beta increase as more factors are added. This is different from what was observed for the biotech portfolio. The size beta is only significant at a 5% level for the Fama-French three-factor and Carhart model. We observe that the SMB loses significance in the five-factor models, which can be due to the significant CMA beta.

Another interesting finding is that the value beta is significantly negative for all multi-factor models except the Carhart model. In the same way as for the biotech portfolio, this can be explained by the correlation with the added momentum factor. This was somehow expected based on the discussion of the model weakness in Chapter 4. In comparison to the biotech portfolio, the RMW beta is not significant at any level for the three most extensive multi-factor models. The CMA beta is significantly positive in all models of presence. This strengthens our conception of that the pharma portfolio is tilted towards stocks with conservative investment strategies.

Finally, we observe that the BAB and QMJ factors are not significant for the pharma portfolio. Thus, these additional systematic risk factors do not help in explaining more of the return. We observe that the Fama-French five-factor model also has the highest explanatory power of the models for the pharma portfolio.

Table 5.10: Pharma Portfolio in Developed Countries with Alternative Factor Models

	Dependent variable: $R^V_{rst} - R_{ft}$				
	FF3	Carhart	FF5	FF5 + Mom	Seven-factor
α	0.190	0.094	0.017	-0.011	-0.115
	(0.212)	(0.217)	(0.213)	(0.217)	(0.239)
β_{MKT}	0.645***	0.671***	0.712***	0.718***	0.729***
	(0.049)	(0.051)	(0.050)	(0.051)	(0.072)
β_{SMB}	-0.374**	-0.368**	-0.279*	-0.282*	-0.307*
	(0.145)	(0.144)	(0.147)	(0.147)	(0.159)
β_{HML}	-0.190**	-0.104	-0.593***	-0.537***	-0.576***
	(0.082)	(0.095)	(0.143)	(0.164)	(0.145)
β_{MOM}		0.168*		0.065	
		(0.093)		(0.094)	
β_{RMW}			0.024	0.023	-0.081
			(0.197)	(0.198)	(0.289)
β_{CMA}			0.868***	0.821***	0.816***
			(0.219)	(0.230)	(0.224)
β_{BAB}					0.148
					(0.119)
β_{QMJ}					0.066
					(0.224)
Observations	150	150	150	150	150
R^2	0.548	0.558	0.594	0.595	0.599
Adjusted R^2	0.539	0.546	0.579	0.578	0.579
Note:					*p<0.1; **p<0.05; ***p<0.01

The table provides the regression results for the pharma portfolio in developed countries with multiple factor models, using monthly return data from January 2010 to June 2022. We apply the generalized formula $R^V_{rst} - R_{ft}$ as the dependent variable, in which r corresponds to Developed Countries, s corresponds Pharma, V denotes that the portfolio is value-weighted, and R_{ft} denotes the risk-free rate. The alpha is the constant term and represents the monthly abnormal return in percent. The betas captures the loadings to the systematic risk factors. MKT is the value-weighted market return minus the risk-free rate. SMB (Small Minus Big) captures the portfolio's exposure to small market cap stocks. HML (High Minus Low) captures the portfolio's exposure to high book-to-market stocks. RMW (Robust Minus Weak) captures the exposure to firms with robust profitabilities. CMA (Conservative Minus Aggressive) captures the exposure to a conservative investment strategy. BAB (Betting Against Beta) captures the exposure to lower beta assets. QMJ (Quality Minus Junk) captures the exposure to quality stocks.

5.4.2 Annually Rebalancing

We continue the robustness analysis by examining the results of annually rebalanced portfolios. We see that the biotech portfolio delivers a significantly positive alpha at a 10%

level with annual rebalancing. The coefficients tell us that the biotech portfolio of stocks in developed countries has delivered an abnormal monthly return of 0.576% on average. This differs from the results with monthly rebalancing. A possible explanation is that the profit of monthly rebalancing is offset by rare but large negative returns. This fits with the high standard deviation we observed for the biotech portfolio in the descriptive statistics. Nonetheless, we cannot reject our first hypothesis as we apply the 5% significance level. The pharma portfolio does not exhibit a significant alpha.

Table 5.11: Regression Results for Annually Rebalanced Portfolios

	Dependent variable: $R^V_{rst} - R_{ft}$	
	Biotech	Pharma
α	0.576*	0.020
	(0.333)	(0.214)
β_{MKT}	0.964***	0.717***
	(0.079)	(0.050)
β_{SMB}	0.907***	-0.284*
	(0.230)	(0.147)
β_{HML}	-1.140***	-0.572***
	(0.223)	(0.143)
β_{RMW}	-1.514***	0.046
	(0.309)	(0.198)
β_{CMA}	-0.286	0.841***
	(0.342)	(0.219)
Observations	150	150
R^2	0.691	0.595
Adjusted R^2	0.680	0.581
Note:	*p<0.1; **p<0.05; ***p<0.01	

The table provides the regression results for the biotech portfolio and the pharma portfolio for stocks in developed countries, using monthly return data from January 2010 to June 2022. We apply the generalized formula $R^V_{rst} - R_{ft}$ as the dependent variable, in which r corresponds to Developed Countries, s corresponds to the sectors, V denotes that the portfolio is value-weighted, and R_{ft} denotes the risk-free rate. The alpha is the constant term and represents the monthly abnormal return in percent. The betas capture the loadings to the systematic risk factors of the Fama-French five-factor model. MKT is the value-weighted market return minus the risk-free rate. SMB (Small Minus Big) captures the portfolio's exposure to small market cap stocks. HML (High Minus Low) captures the portfolio's exposure to high book-to-market stocks. RMW (Robust Minus Weak) captures the exposure to firms with robust profitability. CMA (Conservative Minus Aggressive) captures the exposure to a conservative investment strategy.

Furthermore, we observe that the betas for both the biotech and the pharma portfolio exhibit identical significance levels and almost identical magnitudes as the respective portfolios with monthly rebalancing. This suggests that an investor can achieve similar average risk factor exposures by rebalancing annually compared to monthly. This supports the idea that investors could save trading and management fees by rebalancing more seldom.

5.4.3 Equally-Weighting

We finish the robustness analysis by viewing the results with equally-weighted portfolios. Thus, we view the results when all stocks have the same weight in the portfolio. This can highlight the risk loadings of the smaller firms as opposed to the value-weighted portfolios. The regression results for the equally-weighted portfolios are presented in Table 5.12.

We observe that the alpha is significantly positive for the biotech portfolio. The coefficient suggests that the portfolio has delivered an abnormal monthly return of 0.627% on average. Thus, we can reject our first hypothesis for the equally-weighted biotech portfolio in favor of the alternative hypothesis, *The biotech portfolio* ***does*** *deliver significant abnormal returns*. We observe a significant alpha for the pharma portfolio at a 10% level with a Z-score of 1.791, not too far away from the critical value of 1.96. Nonetheless, we do not reject our second null hypothesis as we apply the 5% significance level.

Moreover, we observe that both the biotech portfolio and pharma portfolio fluctuate more than the market given the betas of 1.112 and 1.022, respectively. This is somehow a surprising result with respect to the pharma sector, which exhibited a market beta well below 1 in the value-weighted portfolio. The result confirms that the large and small pharma firms have different market exposure, while large and small biotech firms have similar market exposures. Furthermore, the size beta is significantly positive for both sectors and more extreme than what was observed earlier with the value-weighted variant. This is expected from the equally-weighted portfolio as it assigns more weight to small firms, which results in a massive size exposure (Swade et al., 2022). The size beta is higher for the biotech portfolio than the pharma portfolio, which seems reasonable given that the firms are mostly small-, micro- and nano-cap stocks.

Furthermore, we observe that the value betas are fairly similar to the value-weighted portfolios. We observe that the significant profitability beta is more extreme for the equally-weighted biotech portfolio. Thus, small biotech firms have even weaker profitability.

Table 5.12: Regression Results for Equally-Weighted Portfolios

	Dependent variable: $R^E_{rst} - R_{ft}$	
	Biotech	Pharma
α	0.627**	0.419*
	(0.309)	(0.234)
β_{MKT}	1.112***	1.022***
	(0.073)	(0.055)
β_{SMB}	1.324***	0.531***
	(0.213)	(0.161)
β_{HML}	-0.904***	-0.604***
	(0.207)	(0.157)
β_{RMW}	-1.886***	-0.859***
	(0.286)	(0.216)
β_{CMA}	-0.717**	0.056
	(0.318)	(0.240)
Observations	150	150
R^2	0.787	0.772
Adjusted R^2	0.780	0.764

Note: *p<0.1; **p<0.05; ***p<0.01

The table provides the regression results for the biotech portfolio and the pharma portfolio for stocks in developed countries, using monthly return data from January 2010 to June 2022. We apply the generalized formula $R^E_{rst} - R_{ft}$ as the dependent variable, in which r corresponds to Developed Countries, s corresponds to the sectors, E denotes that the portfolio is equally-weighted, and R_{ft} denotes the risk-free rate. The alpha is the constant term and represents the monthly abnormal return in percent. The betas captures the loadings to the systematic risk factors of the Fama-French five-factor model. MKT is the value-weighted market return minus the risk-free rate. SMB (Small Minus Big) captures the portfolio's exposure to small market cap stocks. HML (High Minus Low) captures the portfolio's exposure to high book-to-market stocks. RMW (Robust Minus Weak) captures the exposure to firms with robust profitabilities. CMA (Conservative Minus Aggressive) captures the exposure to a conservative investment strategy.

We also observe that the pharma portfolio exhibits a negative profitability beta, which is different from the insignificant beta observed earlier. This indicates that large pharma firms dilute the significant negative profitability beta of smaller pharma firms in the value-weighted portfolio. Lastly, we observe that the investment beta is significantly negative for the biotech portfolio and insignificant for the pharma portfolio. These exhibit the opposite of what was observed for the value-weighted portfolios. In sum, the results from the equally-weighted portfolios show that there are different characteristics of large and small firms in the biotech and pharma sector.

5.5 Limitations of the Analysis

In this section, we will discuss the limitations of the analysis. Limitations concerning data reliability and model weakness have already been addressed in previous sections.

5.5.1 Survivorship Bias

The first limitation is that our data sample is exposed to survivorship bias. There might be firms that are not included in our sample due to bankruptcy, delisting, or mergers and acquisitions. In other words, our data sample only includes firms that have survived since January 2010. This might result in an overestimation of historical performance and cause a positive bias to our results. A conventional stock index would not have this bias because it would account for firms that both join and leave the index. We would need to filter biotech and pharma firms each year throughout the sample period so that we enable firms to join and leave the portfolio, in order to prevent survivorship bias. However, due to the limitations of this thesis, we rather included the S&P Biotechnology and S&P Pharmaceuticals index as a way to control for the survivorship bias.

5.5.2 Private-Owned Firms

The second limitation is that we do not include unlisted firms. The average firm size would likely decrease and the average risk level would increase if we were to include unlisted firms in the sample. This is because they are typically smaller and subject to more financial restrictions than listed firms. Given the relative infancy of the biotech sector, one would anticipate proportionally more unlisted biotech firms than listed ones. Yet, it is uncertain how adding these firms will influence the biotech stock sample in comparison to the pharma stock sample. If true, including unlisted firms in the sample would highlight the contrasts between the two sectors.

5.5.3 Management and Trading Fees

Lastly, we discuss the third limitation. Our analysis has followed an academic approach as we have studied portfolios that include all stocks in a sector. If we were to actually invest in similar sector portfolios, we would have to take management and trading fees into consideration. These fees are related to compensations of investment managers or advisors following up on the investments and (or) the actual transactions of the rebalancing. Given that we have monthly rebalancing, there would be twelve rebalancings annually multiplied by every firm in the portfolio. For June 2022, there would be 1,076 transactions as this is the number of firms in the portfolio of developed countries. From an investor's perspective, it might not be necessary to follow such a systematic rebalancing strategy. The investor's preferences can vary depending on risk appetite, time and budget (Bodie et al., 2020). Nonetheless, one can argue that a sector portfolio must be more closely followed as it is riskier compared to a fully diversified portfolio. Thus, it is also realistic to expect higher management fees, which are compensations to investment managers or advisers for following up on the portfolio of stocks.

6 Discussion

The objective of this thesis has been to answer whether the returns in biotech and pharma stocks have exceeded what would be predicted by financial asset pricing models. This chapter includes a further discussion of the alphas, i.e., the abnormal return findings from our analysis. We will only discuss the alphas that showed significance at a 5% level. As we discuss possible explanations, we should keep in mind that an alpha different from zero indicates that the asset pricing model is insufficient. There might exist other factors than the ones we have controlled for that can explain abnormal returns in the portfolios. This is also given by the explanatory powers of 60-70%. The discussion will focus on possible explanations for the significant alphas, i.e., the abnormal return findings.

Table 6.1: Summary of Alphas

	α	
	Biotech	**Pharma**
Main portfolios		
Developed countries	0.518	0.017
Continent portfolios		
North America	0.131	-0.069
Europe	0.407**	0.191
Time period portfolios		
First 6 years	1.045*	0.357
Last 6.5 years	-0.118	-0.249
S&P 500 sector indices	0.271	-0.136
Robustness analysis		
Fama-French three-factor model	0.006	0.190
Carhart four-factor model	0.003	0.094
Fama-French five-factor model	0.518	0.017
Fama-French five-factor model plus mom	0.480	-0.011
Seven-factor model	0.604	-0.115
Annually rebalancing portfolios	0.576*	0.020
Equally-weighting portfolios	0.627**	0.419*

Note: *p<0.1; **p<0.05; ***p<0.01. The alphas represent the monthly abnormal returns in percentages.

Abnormal Returns of the Value-Weighted Biotech Portfolio in Europe

The first finding is the rejection of the null hypothesis in favor of the alternative hypothesis for the value-weighted biotech portfolio in Europe. That is, *The biotech portfolio **does** deliver positive abnormal returns.* More specifically, we find that the biotech portfolio in Europe delivered a significantly abnormal monthly return of 0.407% after controlling for the exposure to market, size, value, profitability and investment activity. This corresponds to an average annual abnormal return of 5%, which is comparable to the findings of Koijen et al. (2016) in the US. From the literature review, we recall that Koijen et al. (2016) found that firms highly engaged in medical R&D delivered annual abnormal returns of 4-6%. We were not able to confirm similar results for stocks in North America. However, we contribute to the existing literature by confirming similar results for European biotech stocks. Moreover, we are able to confirm that the abnormal return findings of Dong and Guo (2013) for health care services firms in the US also apply to the biotech sector in Europe.

The abnormal return finding raises the potential of a mispricing story for biotech stocks in Europe versus North America. There are several possible explanations for this. First, the fact that North America had almost three times as many biotech firms as Europe, may suggest that the sector is more hyped in North America. Stock prices may have reflected future expectations more sufficiently in North America, which can explain the mispricing of European biotech stocks. Second, the biotech sector is considered younger in Europe than in the US, so there might exist more skepticism toward the new technologies (Cancherini et al., 2021). This seems reasonable given the low hit ratios in R&D projects, making it hard to predict which firms will succeed and which that will fail altogether. In addition, there are long commercialization periods as it takes an average of fifteen years to develop a new drug. This also requires a huge amount of capital (Golec and Vernon, 2009). To control for these risk explanations, one could construct a more sector-specific factor, for instance, an R&D factor. Third, Europe has lagged behind the US biotech market in transforming science into sold products. Some investors suggest that Europe lacks biotech talent and entrepreneurial mindsets, while others point to higher government restrictions (Cancherini et al., 2021). For these reasons, investors in Europe may actively avoid biotech stocks causing mispricing. Hence, those that do invest are able to earn abnormal returns, while those who do not invest, pay a significant financial cost by doing so.

From an ethical perspective, we can argue that the mispricing of biotech stocks in Europe is unfavorable. Underpriced stocks typically attract investors and can potentially increase the availability of capital. Thus, the mispricing gives biotech stocks in Europe more opportunities to continue some of the questionable businesses, such as cloning and the use of human stem cells for the production of organs (Fink, 2017). However, mispricing can also be viewed as beneficial from an ethical perspective. If all ethical investors avoid biotech stocks, those that hold biotech stocks will be indifferent to ethical aspects and will not use their power as investors to influence the ethical aspects of the business. Hence, we can argue that it is preferable that investors are attracted to the underpriced biotech stocks as it then is more likely that ethical parties will invest.

Moreover, we know that alpha is a widely used performance measure. However, a positive alpha cannot guarantee a better Sharpe ratio for a portfolio (Bodie et al., 2020). Nonetheless, the descriptive statistics showed that the biotech portfolio in Europe has a higher Sharpe ratio than the pharma portfolio and the market proxy. This suggests that the biotech portfolio is preferable in terms of risk-adjusted returns.

Abnormal Returns of the Equally-Weighted Biotech Portfolio in Developed Countries

The second finding is the rejection of the null hypothesis in favor of the alternative hypothesis for the equally-weighted portfolio in developed countries. That is, *The biotech portfolio* ***does*** *deliver positive abnormal returns.* The result shows a significantly abnormal monthly return of 0.627% after adjusting for risk factors in the Fama-French five-factor model. The result implies that larger biotech firms dilute some of the alpha generations of smaller biotech firms in the value-weighted biotech portfolio. There are several possible explanations for this finding. First, the significant alpha can indicate a more consistent medical innovation premium amongst small firms (Koijen et al., 2016). Smaller biotech firms are typically in earlier clinical phases and more dependent on external financing (Thakor et al., 2017) compared to large ones. Another explanation is that the equally-weighted biotech portfolio can benefit from short-term reversal as opposed to the value-weighted portfolio. That is, stocks with relatively low (high) returns over the past month earn a positive (negative) abnormal return in the following month's exposure (Swade et al., 2022). The short-term reversal effect might be larger for the biotech portfolio as it is more volatile than the pharma portfolio.

The Mispricing Story Challenges the Efficient Market Hypothesis

The mispricing story of biotech stocks contradicts the efficient market hypothesis. The notion argues that prices reflect all available information, making it impossible to generate alpha. However, it has been shown that "all available information" is not necessarily reflected in all markets, causing varying degrees of efficiency (Bodie et al., 2020). As biotech firms tend to be small there might be relatively little coverage by analysts and the stocks may be less efficiently priced. As we have included all stocks in the sector, there will be different reporting requirements for stocks on smaller stock exchanges. Conversely, it is reasonable to expect pharma firms to be more efficiently priced given that the firms are generally larger and are likely to have more analyst coverage.

Another point is that the progress in the R&D projects is reflected in high stock prices rather than in the balance sheet. According to international accounting standard 38 (IAS 38), R&D fees are only expensed, and internally generated intangible assets cannot be recognized on the balance sheet unless they are acquired (IFRS Foundation, 2001). Hence, it is hard to put a price on R&D projects as product success is hard to predict. The result can be that market prices do not accurately reflect the firms' true values, i.e., inefficient pricing. The inefficient pricing can hold for both pharma and biotech stocks. However, we can argue that there is more efficient pricing of pharma stocks as they typically are the ones to acquire and can recognize the market value of intangible assets on the balance sheet. Nonetheless, we cannot guarantee that our results are due to inefficient financial markets, and not inadequate use of asset pricing models.

No Abnormal Returns for the Pharma Portfolios

The third finding is that none of the pharma portfolios delivered significant alphas at the 5% level. Thus, we keep the null hypothesis in favor of the alternative hypothesis, *The pharma portfolio* ***does not*** *deliver positive abnormal returns.* This aligns with the observations of Thakor et al. (2017) in the periods 2000-2004 and 2005-2009 in the US. Even so, it contradicts the observations of Thakor et al. (2017) of pharma stocks leading up to 2000. As Thakor et al. (2017) studied stocks from 1930 to 2015, we have results revealing that circumstances have changed in recent years. The insignificant alpha for the pharma portfolio reveal that there are no longer unobserved factors that have a direct positive relationship with the significant systematic risk factors of the portfolio. Nonetheless, there can exist abnormal returns among individual pharma firms but we are not able to detect abnormal returns for the sector as a whole. A possible explanation could be that the industry has reached the maturity stage of the industry life cycle. Industry leaders have emerged, but at the same time, there might still be surviving firms from the growth stage that aim to reach their full potential (Bodie et al., 2020). In other words, market growth has slowed and the firms are more different from one another. Thus, pharma firms are exposed to more individual unsystematic risks, which explains the insignificant alpha and the relatively low R-squared.

7 Conclusion

The objective of this thesis is to answer whether the returns of biotech and pharma stocks have exceeded the expectations of financial asset pricing models. As previous research reported inconsistent results, we considered this an interesting topic. We studied pharma and biotech stocks in developed countries from 2010 to 2022 and will highlight our most important findings.

In terms of risk factor exposure, we have observed that both pharma and biotech stocks are positively exposed to the market factor and negatively exposed to the value factor. Generally, pharma stocks exhibited less extreme exposure to these factors than biotech stocks. Additionally, the biotech portfolio was positively exposed to the size factor and negatively exposed to the profitability factor. The pharma portfolio was positively exposed to the investment factor.

Our two main findings are that the value-weighted biotech portfolio in Europe and the equally-weighted biotech portfolio in developed countries deliver significant abnormal returns. Some investors may actively avoid biotech stocks due to the many risks. Hence, those that do invest are able to earn abnormal returns. Our discussion suggests that R&D activity represents an unaccounted systematic risk factor. Thus, we encourage future studies on a R&D factor. Our results are in line with Dong and Guo (2013) findings for health care service firms, as well as Koijen et al. (2016) findings for biotech, pharma and health care equipment firms. As these studies were conducted on US stocks, we contribute to the existing literature by suggesting similar results for European biotech stocks.

Our results suggest no significant abnormal returns for the pharma portfolios. Thus, there are no unobserved factors that have a direct positive relationship with the significant systematic risk factors of the pharma portfolio. Our results contradict the findings of Thakor et al. (2017) for pharma stocks leading up to 2000. Overall, our findings are intriguing for anyone interested in investing in health care, especially in biotech and pharma stocks in developed countries.

As we review our thesis as a whole, we recall the bold statement of our title: *Biotech - the end of big pharma?* We leave this open for interpretation, but one suggestion might be that *biotech is the beginning of big biopharma*.

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Appendix

A1 Model Testing

We conduct a number of tests to ensure that the Gauss-Markov assumptions and the stationarity criterion are upheld in order to determine whether there are any issues related to our regressions, and thereby results.

A1.1 Portfolio Distribution

First, we want to check if the normality assumptions are satisfied for all our portfolios. We examine the distribution of residuals of our portfolios by looking at their respective histograms and density lines, as well as QQ-plots. Figure A1.1 to A1.6 shows that all our data is normally distributed around zero and there is limited skewness.

Figure A1.1: Histogram and QQ-plot of Model Residuals, Developed Countries Portfolios

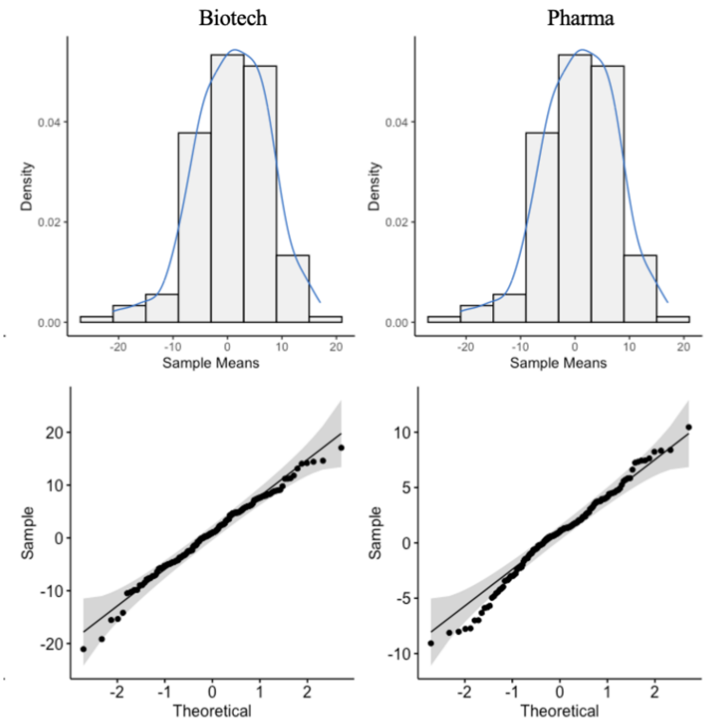


Figure A1.2: Histogram and QQ-plot of Model Residuals, North America Portfolios

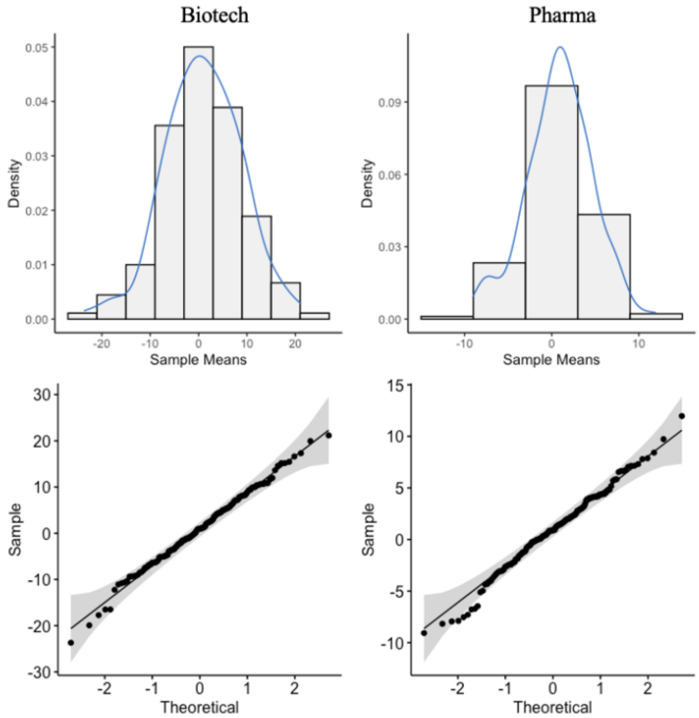


Figure A1.3: Histogram and QQ-plot of Model Residuals, Europe portfolios

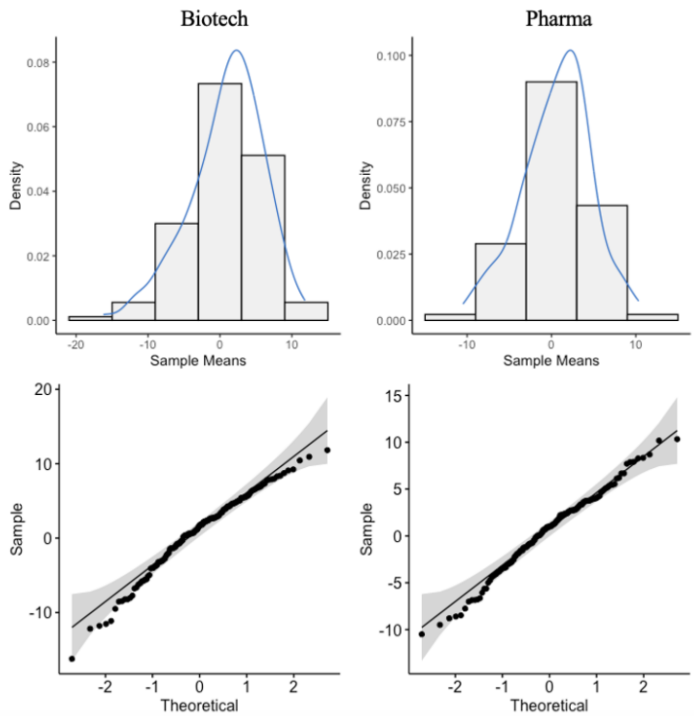


Figure A1.4: Histogram and QQ-plot of Model Residuals, First 6 Years Portfolios

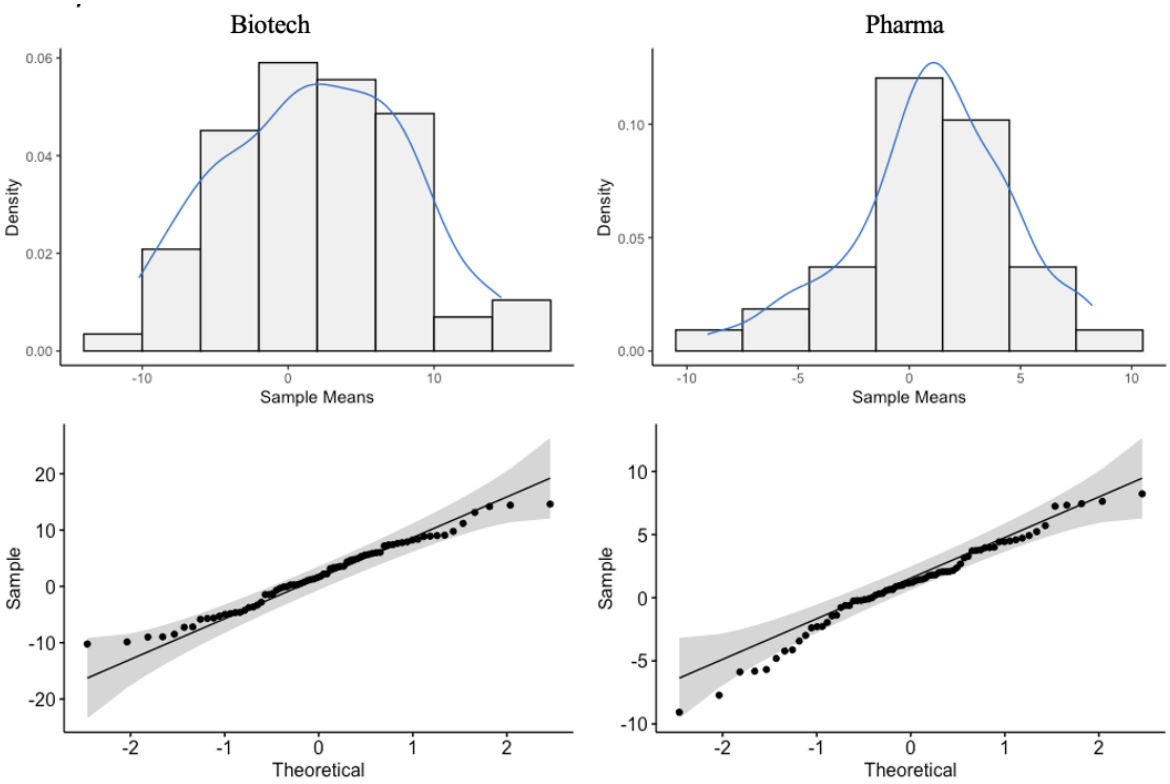


Figure A1.5: Histogram and QQ-plot of Model Residuals, Last 6.5 Years Portfolios

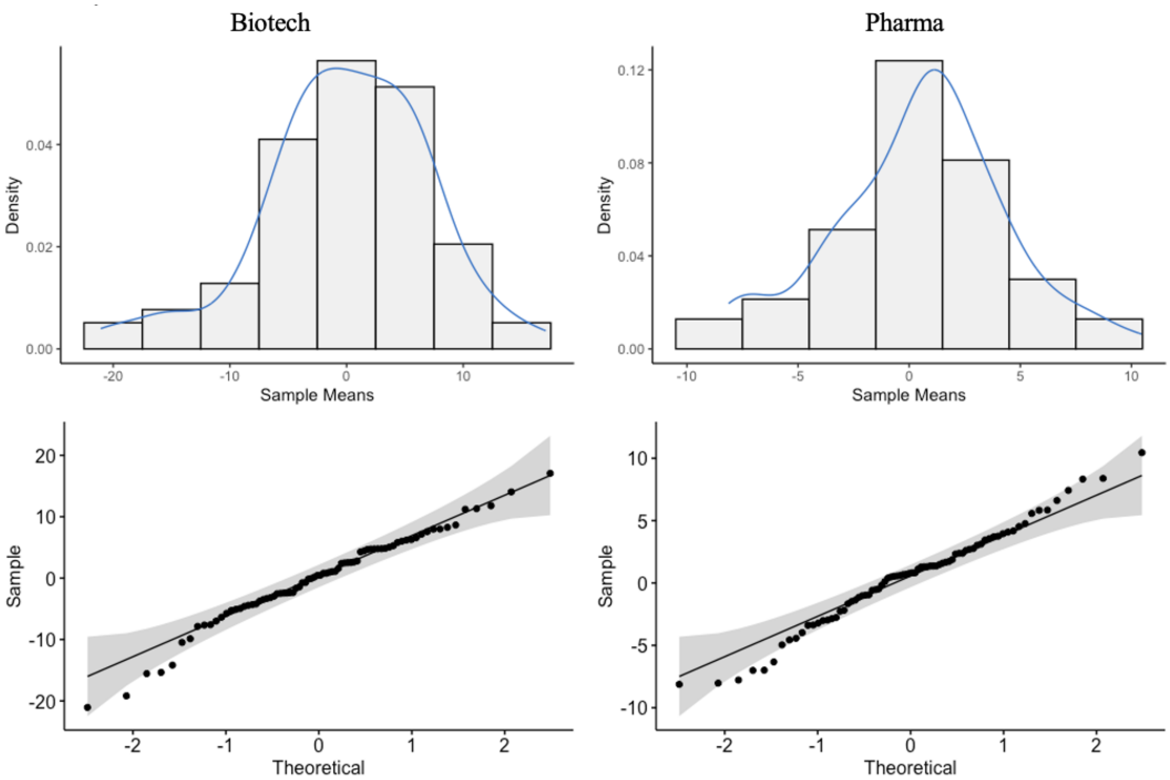


Figure A1.6: Histogram and QQ-plot of Model Residuals, Biotech S&P 500 Portfolios

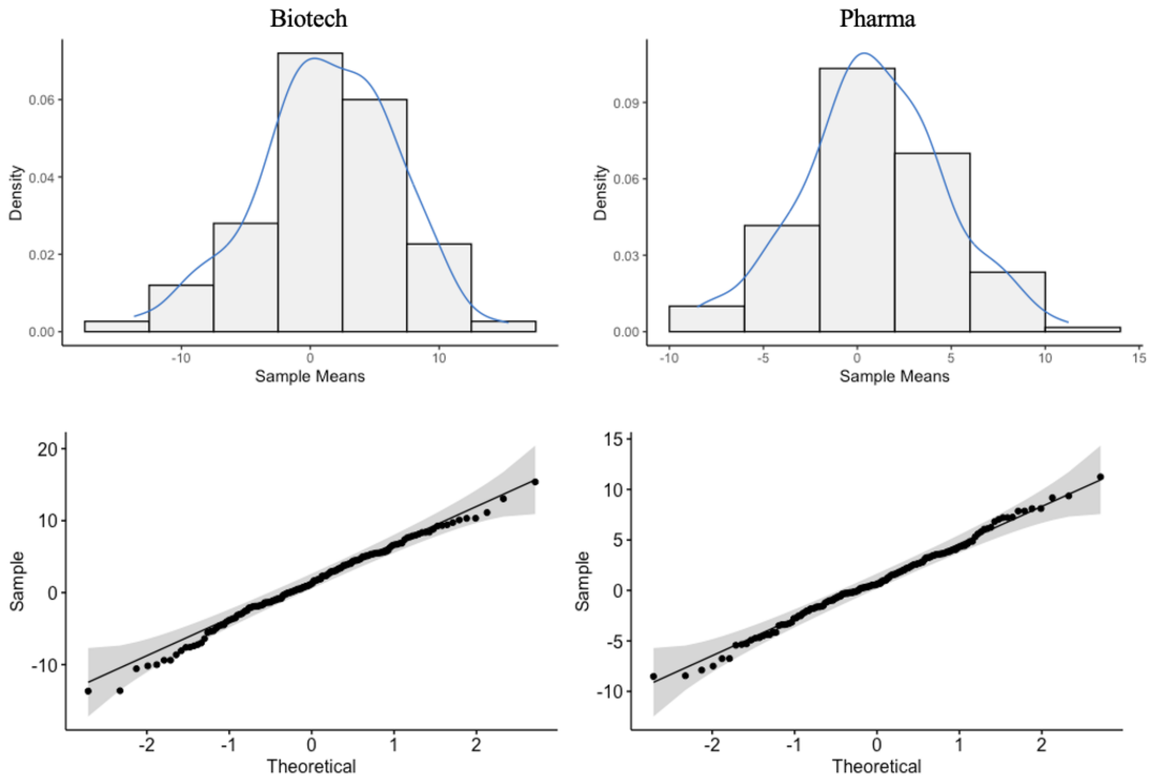


Figure A1.7: Histogram and QQ-plot of Model Residuals, Equally-Weighted Portfolios

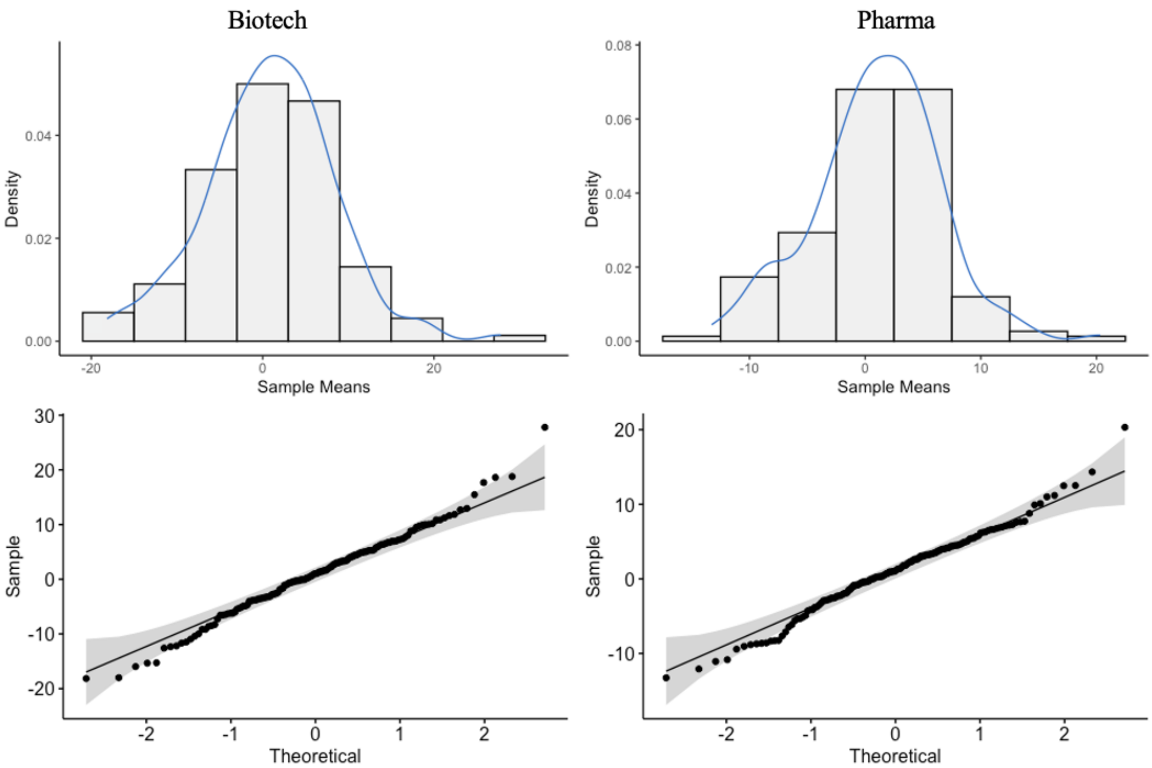
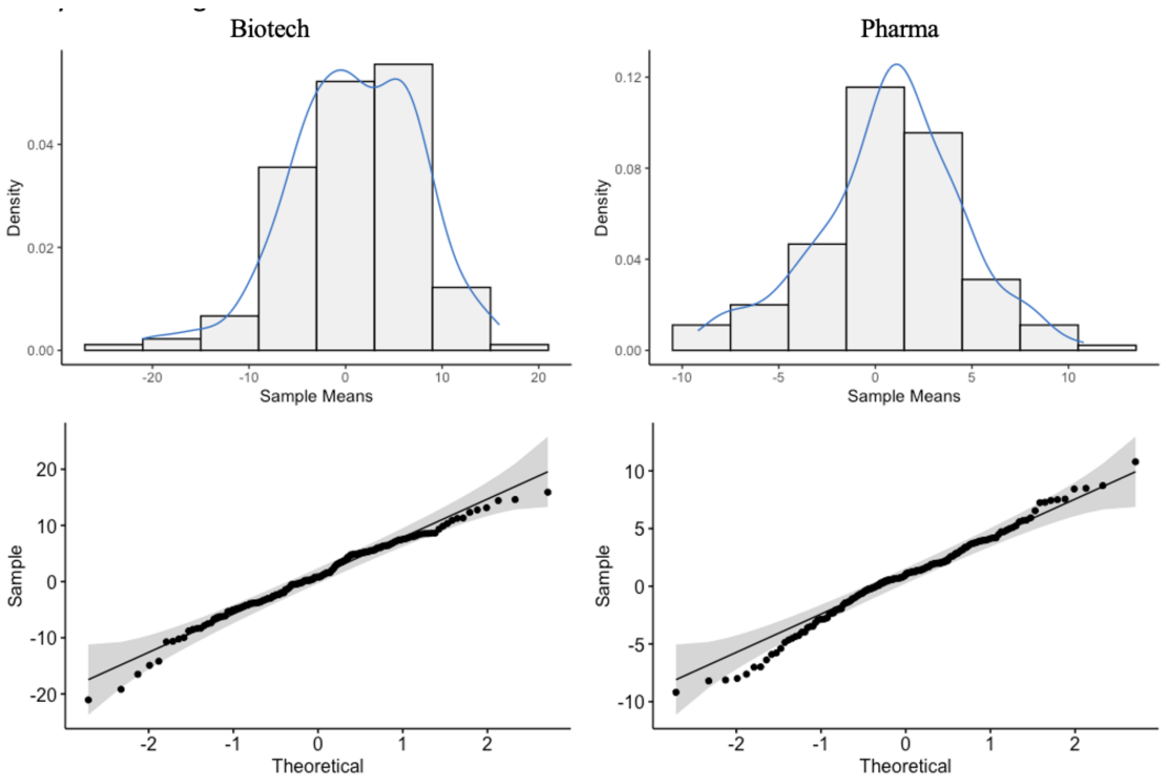


Figure A1.8: Histogram and QQ-plot of Model Residuals, Yearly Rebalanced Portfolios



A1.2 Breusch-Pagan Test for Homoscedasticity

Table A1.1 presents the results of the Breusch-Pagan test applied to all of our portfolios to test for homoscedasticity. The test statistic, designated as "BP" in the table, has a chi-squared distribution. The assumption of homoscedasticity, or equal error variances, is the null hypothesis. The P-values above 0.05 in the table suggest that we cannot reject the null hypothesis of homoscedasticity. As a result, we draw the conclusion that our data are not heteroscedastic. In other words, when performing hypothesis testing based on our portfolios, there is no need to change the standard errors for heteroscedasticity (Wooldridge, 2012).

Table A1.1: Breusch-Pagan Test for Homoscedasticity

	Biotech		**Pharma**	
	(BP)	**P-value**	**(BP)**	**P-value**
Fama-French Three-Factor	2.475	0.649	3.776	0.287
Carhart	2.475	0.649	3.081	0.544
Fama-French Five-Factor				
Main portfolios	3.034	0.695	1.317	0.933
Regional portfolios				
Biotech North America	3.493	0.625	2.938	0.710
Biotech Europe	1.130	0.951	1.459	0.918
Time period portfolios				
First 6 years	7.502	0.186	4.947	0.422
Last 6.5 years	1.427	0.921	2.489	0.778
S&P 500 Indices	4.296	0.654	1.373	0.927
Equally-Weighted	6.184	0.289	4.344	0.501
Annual Rebalancing	3.105	0.684	1.251	0.940
Fama-French Five-Factor + MOM	3.249	0.777	2.038	0.916
Seven-Factor	3.635	0.821	2.644	0.916

A1.3 Breusch-Godfrey Test for Autocorrelation

Table A1.2 presents the results of the Breusch-Godfrey test for autocorrelation. The coefficient estimations are unaffected by autocorrelation. In other words, the coefficient estimations remain accurate (Wooldridge, 2012). However, if autocorrelation is present, standard errors and statistical tests must be corrected for it. The test statistic is shown in the table below by "LM". The null hypothesis is that there is no autocorrelation in our portfolios. Hence, a large test statistic and a P-value below 0.05 indicates that something is wrong.

We cannot reject the null hypothesis for any of our portfolios due to the P-values above 0.05. Therefore, we draw the conclusion that autocorrelation in our data set is not a concern.

Table A1.2: Breusch-Godfrey Test for Autocorrelation

	Biotech		**Pharma**	
	(LM)	**P-value**	**(LM)**	**P-value**
Fama-French Three-Factor	0.004	0.948	0.007	0.798
Carhart	0.004	0.948	0.015	0.904
Fama-French Five-Factor				
Main portfolios	0.246	0.620	1.317	0.933
Regional portfolios				
North America	0.815	0.366	1.585	0.208
Europe	0.664	0.415	0.997	0.318
Time period portfolios				
First 6 years	0.172	0.678	0.118	0.730
Last 6.5 years	1.069	0.301	0.978	0.323
S&P 500 Indices	0.668	0.414	0.226	0.6335
Equally-Weighted Portfolios	3.264	0.071	0.811	0.368
Annual rebalancing	0.009	0.920	0.021	0.885
Fama-French Five-Factor + MOM	0.293	0.588	0.001	0.974
Seven-Factor	0.208	0.648	0.001	0.841

A1.4 Augmented Dickey-Fuller Test for Unit Root

Table A1.3 and A1.4 shows the results from the augmented Dickey-Fuller test for stationarity for all the dependent and independent variables used in our regressions. The test statistic, "DF", should be less than a selected critical value. The null hypothesis is that the data is non-stationary, i.e that a unit root is present. Consequently, a high P-value suggests that there is a problem.

We clearly reject the null hypothesis for all of our tests at a 5% level based on the tables' low P-values for our portfolios and risk factors. As a result, we conclude that all of our variables are stationary and may be used without issue in OLS regressions.

Table A1.3: Augmented Dickey-Fuller Test for Unit Root, Dependent variables

	Biotech		Pharma	
	(DF)	**P-value**	**(DF)**	**P-value**
Dependent Variables				
Main portfolios	-8.139	0.01	-9.636	0.01
Regional portfolios				
North America	-8.171	0.01	-9.769	0.01
Europe	-8.607	0.01	-9.344	0.01
Time period portfolios				
First 6 years	-5.932	0.01	-6.252	0.01
Last 6.5 years	-4.803	0.01	-7.136	0.01
S&P 500 Indices	-8.778	0.01	-10.765	0.01
Equally-Weighted	-7.917	0.01	-8.519	0.01
Annual Rebalancing	-8.181	0.01	-9.767	0.01

Table A1.4: Augmented Dickey-Fuller Test for Unit Root, Risk Factors

	Developed countries		North America		Europe	
	(DF)	**P-value**	**(DF)**	**P-value**	**(DF)**	**P-value**
Risk Factors						
Rm-Rf	-9.381	0.01	-9.462	0.01	-9.197	0.01
SMB	-7.949	0.01	-7.724	0.01	-8.561	0.01
HML	-7.266	0.01	-6.980	0.01	-8.201	0.01
RMW	-9.067	0.01	-9.202	0.01	-9.026	0.01
CMA	-6.724	0.01	-6.445	0.01	-7.206	0.01
MOM	-9.682	0.01	-9.293	0.01	-9.794	0.01
BAB	-10.069	0.01				
QMJ	-8.508	0.01				

A2 Multicollinearity

A2.1 Correlation Matrix

Table A2.1 shows the Pearson correlation coefficients for the Fama-French risk factors for North America and Europe applied to our regressions as explanatory variables. A correlation of 1 indicates a strong positive relationship, a correlation of -1 indicates a strong negative relationship, and a correlation of 0 indicates no relationship between the coefficients. The table shows that the majority of the variables are correlated, but not to an extent where multicollinearity becomes a problem. The HML and CMA risk loadings have the highest correlation in North America with 0.784. In Europe, we find the highest correlation of -0.806 between the HML and RMW risk loading. According to Ratner (2009)[15], multicollinearity for these risk loadings may be an issue, which could weaken the statistical power of our regression models.

Table A2.1: Pearson Correlation Coefficients for Fama-French Risk Factors

	Mkt	SMB	HML	RMW	CMA	MOM
North America						
Mkt	1.000					
SMB	0.397	1.000				
HML	0.020	0.229	1			
RMW	-0.147	-0.485	-0.177	1.000		
CMA	-0.101	0.050	0.784	-0.004	1.000	
MOM	-0.210	-0.235	-0.451	0.077	-0.232	1.000
Europe						
Mkt	1.000					
SMB	0.072	1.000				
HML	0.397	-0.044	1.000			
RMW	-0.318	-0.010	-0.806	1.000		
CMA	-0.024	-0.199	0.682	-0.534	1.000	
MOM	-0.385	0.002	-0.595	0.485	-0.226	1.000

A2.2 The Variance Inflation Factor

We use the variance inflation factor (VIF) to further test whether multicollinearity is a problem in our data. There have been several recommendations for the maximum limit of the VIF value. For instance, Hair et al. (1995) suggested a maximum level of 10, while Rogerson (2001) suggested a maximum level of 5. Regardless, table A2.2 illustrates that multicollinearity is not a major issue for our explanatory variables because they are all below 5. As a result, we run our regressions using all the variables. However, when

[15] Correlation coefficients between ± 0.7 and ± 1 are categorized as high, and implies strong correlation (Ratner, 2009).

interpreting the regression results, we keep in mind the findings from the correlation matrix.

Table A2.2: The Variance Inflation Factor for the Fama-French Risk Factors

	VIF (Developed)	**VIF (North America)**	**VIF (Europe)**
Rm-Rf	1.193	1.246	1.481
SMB	1.149	1.596	1.066
HML	4.427	3.562	5.791
RMW	1.617	1.363	2.878
CMA	3.109	2.927	2.588
MOM	1.612	1.388	1.722