Real estate, risk, return and optimal portfolios

Exploring the Position of residential real estate in asset pricing frameworks and optimal portfolios

Jeppe Helgesen

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Preface

This thesis marks the end of five years at the University of Bergen. First, I would like to thank my supervisor, Hans K. Hvide, for his guidance and advice during the writing of this thesis. Second, I would also like to thank my family, friends, and particularly my girlfriend for their unwavering support and thorough revisions. Lastly, I would like to thank my fellow students at the Department of Economics. It has been five great years at the University of Bergen, and you are the reason behind that.

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Abstract

This master's thesis contributes to the understanding of optimal portfolio diversification by examining the position of residential real estate. By incorporating the principles of Modern Portfolio Theory, including Markowitz’s portfolio theory, CAPM, and FF3, the thesis provides an in-depth analysis of risk, return, and diversification possibilities. Moreover, by considering the lasting effects of the Global Financial Crisis, the thesis sheds light on the interplay between risk, rare events, and real estate. The results reveal that the real estate sector exhibits relative stability when looking at systematic risk in both asset pricing models, although it is prone to rare extreme events increasing risk significantly. The risk-return estimates are further compared with the results from creating optimal portfolios. The optimal portfolio position of real estate is ambiguous because of the GFC. However, it is clearly beaten by sectors such as consumer staples and healthcare, being sectors with low risk and higher expected returns than real estate. At the same time, riskier sectors like consumer discretionary are also chosen over real estate, as they have better risk-return relationships. The analysis also finds that sectors with high relative volatility maintain the same relative position when considering systematic risk.

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1 Introduction

Optimal portfolio diversification is a focal point for investors who aim to balance the relationship between risk and return. I will in this thesis highlight the position residential real estate holds in optimal portfolios, considering the risk profile associated with real estate investments and the impact of rare events such as the Global Financial Crisis (GFC). Real estate investments possess distinctive attributes that differentiate them from traditional financial assets like stocks and bonds. The physical nature of the real estate, combined with its income-generating and value-appreciating potential, can be assumed to make it an appealing option for diversification. However, the risk profile of real estate encompassing both market volatility, liquidity, and property-specific risk is more ambiguous, which necessitates a comprehensive evaluation of its position within a diversified portfolio.

The research question of the thesis is as follows: "How does real estate fit into the choice of optimal portfolio diversification, and by extension, how does the risk-return relationship of real estate compare to the risk-return relationship of other GICS[1] sectors?".

The thesis focuses specifically on residential real estate, which is assumed to be the most direct real estate investment channel for retail investors seeking investment opportunities beyond traditional financial markets. By delving into the position of residential real estate within portfolio diversification, this thesis aims to shed light on the advantages, challenges, and considerations associated with investing in this asset class. To proxy the real estate sector, I utilise data from residential Real Estate Investment Trusts (REITs)[2] as a representative sample. By utilising all the Global Industry Classification Standard (GICS) defined sectors, the analysis provides a comprehensive evaluation of the role of residential real estate within optimal portfolio diversification. Moreover, the principles of Modern Portfolio Theory will be incorporated to examine the position residential real estate has within portfolio diversification. Markowitz (1952) portfolio theory, along with the Capital Asset Pricing Model (CAPM) by

[1] Global Industry Classification Standard.
[2] REIT is an abbreviation of Real Estate Investment Trust and is a company that invests in real estate, which can be invested in by retail investors like any other normal stock.

Sharpe (1964) and Lintner (1965) and the Fama-French Three-Factor Model (FF3) by Fama and French (1992), will serve as analytical frameworks for the analysis. These analysis techniques allow for assessing the risk, return, and diversification benefits of incorporating residential real estate into an investment portfolio.

The second chapter will go into detail, covering the US housing market and its price formation, the stock market and REITs. The third chapter covers the data collection and preparation process and the sources used, with accompanying descriptive statistics. The fourth chapter covers the methodology and theory behind the models while going into depth surrounding the implications of their usage. The fifth chapter presents the results of the analysis with an accompanying discussion. Chapter Six discusses the issues surrounding time and data limitations, statistical errors, and their implications for the analysis. Lastly, Chapter Seven summarises and concludes the thesis.

2 Real Estate in the Literature

2.1 The Underlying Real Estate

Various factors determine the price of real estate over longer periods on a more local level in what is referred to as MSAs[3]. For example, Capozza et al. (2002) bring up local determining factors, including employment growth, the income equality of an area, and specifically, the high serial correlation in house prices in metro areas with higher relative real income, population growth and construction costs. Furthermore, the quality of neighbourhoods generally also plays a significant role, according to Haurin and Brasington (1996). They argue that demand is higher in neighbourhoods with low crime rates, good schools, and short distances to business districts, among other things increasing the general quality of life. Additionally, tax policy and demography are believed to affect MSA real estate demand and prices, see Poterba et al. (1991).

On a macroeconomic level, the effects of monetary policy are argued to play a more central role with the rationale of relaxed monetary policy leading to increased demand for housing and, thereby, mortgages for financing. It is argued that monetary expansion can fuel inflation rates which reinforce growth in house prices, monetary expansion, and credit (such as mortgages), which then leads to further monetary expansion (Goodhart & Hofmann, 2008). However, the relationship between house prices and monetary policy is believed to be more complex, with Del Negro and Otrok (2007) finding a pattern of local factors in large part being the driving force behind MSA house price growth, with monetary policy playing a smaller role in the long-term.

2.1.1 The role of Mortgages, Appraisal Bias and Real Estate Agents

It is argued by Jordà et al. (2016) that households in the US are highly leveraged and that mortgage credit affect the business cycle in the post-WW2 period, slowing down growth rates after credit booms gone bust. The implication from Jordà et al. is that most of the growth in the financial sector in many countries can be attributed to increased household mortgage credit.

[3] MSA is an abbreviation of Metropolitan City Area, which refers to an urban and densely populated area.

As mentioned, the uptake of mortgages and, thereby, increase in household debt can in part be connected to relaxed monetary policy; the consequence is that when monetary policy tightens and interest rates increase, some of the mortgages might default. These mortgages may also be influenced by appraisal bias, as argued by Nakamura (2010), with positive bias being the most common and leading to overvaluation of the property, thereby increasing the size of the mortgage that can be used as financing. Consequently, the mortgage exceeds the property value estimated through the quantitative measure known as the "comparables" method[4] Pagourtzi et al. (2003). As the mortgage lenders themselves can conduct the appraisal, they tend to overvalue the property to please homeowners and hold on to satisfied customers, according to Nakamura. This will likely be most common in countries utilising market-based valuation of properties and loans/mortgages, as a broker then can set the value of the property he is hired to help sell. Market-based valuation of loans is the case in the US (Tsatsaronis & Zhu, 2004). If the mortgage exceeds the property value, it becomes riskier given a tightening of monetary policy. It can impact the real estate sector significantly if leverage rates are higher than they should be given the overvaluation of properties. However, the effect of appraisal bias is ambiguous and difficult to quantify, which creates uncertainty surrounding the quantitative effect of real estate valuation and accompanying bias.

The effect of Real Estate Agents on house prices is of interest in the price formation puzzle. Levitt and Syverson (2008) find that given the information advantage of the Real Estate Agents[5], they are able to sell their privately owned real estate at a premium over their clients, meaning they put in less effort for their clients. However, a clear point in the literature is that intermediaries[6] can reduce the time on the market (Baryla & Ztanpano, 1995; Bernheim & Meer, 2008). Lastly, Allen et al. (2015) find that the monetary gains from services provided by a brokerage are ambiguous, which can be influenced by the mentioned information asymmetry.

The effects of the different parts of the price determination puzzle for the underlying real estate asset are interesting, and even more so, given the ambiguity and scope of some of the

[4] The "comparables" method assumes that the price of a given house is similar to recently sold houses in the same area. Using sales data from recently sold houses the appraiser chooses a set of properties such as age, size, and construction quality among others for us in comparison.

[5] Referring to the intermediary of a real estate transaction, representing either the buyer or seller.

[6] Referring to not only real estate agents, but also realtors and brokerages.

factors. This is also where the connection with the REIT stocks is harder to establish, as the REIT stocks are connected to the performance of the underlying real estate but not to the mortgage uptake of households and the effect of real estate agents. Only having a connection to the real estate investment itself, the rental income, and costs associated with the ownership; see Chapter 2.2 for further elaboration.

2.2 The Stock Market Proxy

REIT data used as a proxy for real estate is traded on the New York Stock Exchange (NYSE). Although the REIT stocks and the underlying real estate can be defined as assets generating a cash flow while being traded in financial markets (REITs through specific regulations and real estate through the possibility of rental income), they differ in how liquid they are, with stocks being highly liquid and real estate being highly illiquid. The reason is that real estate has a maturity on the investment similar to corporate bonds when considering the holding period. Investment in real estate does not function in such a way where one buys and sells a house within a short period, like a week, while that could be done with REIT stocks. The REIT stocks are, in essence, more similar to the stock market, though having a very different dividend policy, as they are obliged to pay out 90 % of their taxable income as dividends to qualify as a REIT (NAREIT, n.d.). The income for a REIT is based on the same factors as direct ownership of a real estate asset, being rental income minus possible costs[7], and therefore it can be assumed to be correlated with real estate. So the argument is that while REIT stocks will have a higher contemporaneous correlation with the stock market, they have a higher long-term correlation with the underlying real estate, making them the most optimal proxy for real estate available (Hoesli & Oikarinen, 2012). Therefore, the residential REIT portfolio is chosen as the optimal proxy for the underlying real estate, as it is assumed that a retail investor would choose to invest in residential real estate over some of the other REIT industries, like offices and hotels if they were to invest directly in the underlying asset.

Of most importance is how the stock market and, by extension, the REIT stocks might fluctuate differently than real estate. It is for example, argued that asymmetric information

[7] The REITs are obligated to earn 95 % of their income through rental income, meaning they cannot be a regular seller of real estate Semer, S. L. (2009). A Brief History of US REITs. *Can. Tax J.*, *57*, 960. . This implies that there is no limit on how much property can be bought.

and adverse selection costs play a large role in creating diversions from fundamental stock values, see Brennan and Subrahmanyam (1995). The stock market, similar to real estate, is influenced by monetary news and changes (Hardouvelis, 1987). As expansionary policy is found to increase stock returns as argued by Thorbecke (1997), possibly because it makes credit cheaper and more easily accessible. Meaning that the stock market, similar to real estate, is influenced by some asymmetric information, with macroeconomic changes also having an impact. The defining difference becomes the liquidity of each asset, with the addition of the previously mentioned ambiguity surrounding differences in how asymmetric information influences the pricing of each asset.

2.2.1 The Great Financial Crisis and Survivorship Bias

Influence from the GFC is of interest as it raises an important issue regarding portfolio creation using the REIT data: the possibility of survivorship bias. If numerous REITs faced bankruptcy during the GFC, the data could be impacted because only the surviving REITs, which were the strongest ones, would be included. In simpler terms, the data would be positively biased as the worst-performing REITs would no longer be present.

A study conducted by Sun et al. (2015) investigated the behaviour of REITs during the GFC. Firstly, they observed that the stock prices of equity REITs exhibited greater volatility than the underlying house prices. They also examined the dispersion of returns across different REITs during the crisis, specifically focusing on their capital structures. Their analysis revealed that REITs with higher debt-to-equity ratios and shorter debt maturity experienced more significant declines in their stock prices during the crisis. Moreover, these companies were compelled to sell off more properties and assets during the period of financial distress, despite a substantial market rebound following the crisis. It is worth noting that Sun et al. reported only a small number of bankruptcies among these REITs during the period.

Given the limited literature available on REIT bankruptcies and the challenges associated with obtaining relevant data, this thesis assumes, based on the findings of Sun et al., that there is, at most, a low degree of survivorship bias in the REIT data, which will not need correction. This assumption aligns with the claims made by NAREIT (National Association of Real

Estate Investment Trusts) saying that REITs were not significantly affected by the crisis (Mattson-Teig, 2020).

3 Data and Descriptive Statistics

3.1 Data collection

This thesis utilises data from various sources, with historical stock data being obtainable from Yahoo Finance. Any other data related to the stocks is not available in a historical format, meaning it has been collected elsewhere. Data used in the factor loadings are downloaded from the Kenneth French website, with the S&P500 also obtained from Yahoo Finance. In addition, two house price indices are obtained, one from the Federal House Financing Agency (FHFA) website and one created based on the city-specific Case-Shiller MSA indices collected from the Federal Reserve Bank of St. Louis (FRED) website. Additional macroeconomic explanatory factors were collected from FRED but did not end up being used in the thesis. The data has a monthly frequency, with the data series covering the period 2000-2022, and this will be the case for all the data used in the thesis unless otherwise specified.

Data used to construct tables and figures are reported in this chapter. In a few cases, figures are created to visualise a point and are not made with data included in the primary dataset and, therefore, not reported in this chapter. Any data source used outside of the data chapter will be appropriately referenced when used.

Sector stock data

The stock data was web scraped[8] from Yahoo Finance using Python libraries in April 2023 (Yahoo Finance, n.d). As web scraping is complicated and time-consuming, the program was limited to collecting 150 stocks from each GICS[9] sector, except for the Real estate sector, having been collected manually in March 2023. To make the program effective, sector-specific tickers were scraped from the webpage Disfold, as their website provides a sector overview where the stocks are sorted in descending order based on market capitalisation (Disfold, n.d). Based on the GICS classification, I used seven of the sectors while collecting the remaining four under “other”, which includes the communications, utilities, basic materials, and energy sectors. The reason the last four sectors were included together is based

[8] A web scraper can get access to a URL and use it to loop over and collect, information that has been predefined. Like the period for a specific stock ticker and the frequency it needs to get it in.
[9] Global Industry Classification Standard.

on the functioning of the web scraper. When the tickers are scraped from the Disfold website, the program does not recognise if the stock has been delisted, so when the ticker is used to scrape Yahoo Finance afterwards, it reports an error code. Additionally, given the low number of stocks with sufficient historical data in the four sectors, they were combined, amounting to four sectors times 150 tickers, equalling 149 stocks. The above reason is also why the other sectors' portfolios consist of different amounts of stocks. Once all the stocks available in a sector are collected, they are averaged together monthly, turning them into an undiversified sector portfolio.

The REIT data was, as mentioned, collected before the rest of the stock data, as it was used in bigger parts of the analysis. It was manually downloaded from Yahoo Finance, based on the stocks in the residential REIT industry. As it only includes the specialised residential stocks in the REIT portfolio, it also becomes the portfolio with the lowest number of stocks. Any residential REIT stock that did not mainly deal in housing was removed; this included REITs with sizeable dealing in marinas, camping and similar parks. Table 3.1 reports the sectors, part of their industry composition and the % of total companies on the stock market the sector represents. The financials sector is the biggest representing 26.9% of the total stock market, though the % of total companies on the market is not based on market cap. Additionally, the % refers to the sector as a whole and not the subset of stocks collected in the dataset.

Table 3. 1 Global Industry Composition Standard

Defined in accordance to addition to the dataset:			
	N - Stocks	**Index industry composition**	**% of total companies on stock market**
REIT	11	Consisting solely of Residential REIT stocks	4,01
Financials	83	Banks, Shell companies, asset management, capital markets etc	26,9
Healthcare	65	Biotech, drug manufactuirers, medical devices, D&R etc	17,95
Tech	59	Software (application & infrastructure), IT services etc	11,96
Consumer Staples	73	Packaged foods, household/ personal products, beverages etc	4,33
Consumer Discretionary	81	Specialty retail, restaurants, auto parts, leisure etc	7,89
Industrials	100	Industrial machinery, aerospace & defense, conglomerates etc	11,25
Other	149	Communications, Utilities, Basic Materials & Energy	15,7

Note: The table presents some of the industries the sectors consist of it also presents what % of the total companies on the stock market the sector represents.

Risk factors

The data for the Fama-French 3-factor model, including the risk-free rate, small minus big factor, and high minus low factor, were obtained from the data page of Kenneth French's website (French, 2023). The S&P500, which also is included in the risk factors as a part of the market risk premium, being the market return minus the risk-free rate, was, as mentioned, obtained from Yahoo Finance like the rest of the stock data.

The real estate factor used in the asset pricing models is created using two different indices where the relevance of each index will be tested in the analysis. The FHFA index captures repeat sales on single-family homes in the US and is downloaded from the FHFA data page (FHFA, 2023). Similarly, the Case-Shiller MSA index captures MSA effects from seventeen big city areas, with each area independently downloaded from the FRED website (S&P Dow Jones Indices LLC, 2023a).

Additional data

Since data on market capitalisation, debt, assets, and liabilities were unavailable for download from Yahoo Finance and otherwise locked behind paywalls, the data source chosen was the website CompaniesMarketCap (CompaniesMarketCap, n.d). The webpage supplies an overview of firm-specific numbers, including the data of interest. The data was collected manually and was only available at a yearly frequency from 2001-2022. The data is used to create weighted portfolios and estimate the unlevered beta values from CAPM and FF3 regressions.

The main issue with the website is that it has protection against web scraping, making it too difficult to collect the data for each stock in each sector manually. Therefore, it was only collected for the REIT data. Additionally, there is the question of the website's validity, given that it does not explicitly report its sources. However, given a few manual checks, the data is seemingly similar to data from more limited but trustworthy sources.

Lastly, data was also collected for US 30-year mortgage rates (Freddie Mac, 2023), the fed rate (Board of Governors of the Federal Reserve System (US), 2023), the inflation rate (U.S. Bureau of Labor Statistics, 2023a) and the unemployment rate (U.S. Bureau of Labor Statistics, 2023b) from FRED. However, this data did not end up being used in the analysis but could be used in future sensitivity analysis.

3.2 Data Preparation

3.2.1 The distribution of the data

The four moments of a data distribution are the mean, variance, skewness and kurtosis. The first moment is an indication of the central tendency of the data, the second moment indicates the deviation from the central tendency. The third moment indicates if the distribution is asymmetric towards the left or right, and the fourth moment indicates the peakiness or flatness of the distribution, referring to the size of the distribution near the peaks or the tails (Press, 1992).

The first moment is the mean, defined as:

$$\mu = \frac{\sum_{i=1}^{n} Y_i}{n} \tag{3.1}$$

The second moment is the variance, defined as:

$$\sigma^2 = \frac{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}{n-1} \tag{3.2}$$

The square root of the second moment is typically taken to get the standard deviation which is the common measure of volatility when assessing assets. In the equation, similar to the equations following it, the $(Y_i - \bar{Y})$ parentheses measures the value of a variable i minus its mean and n is the number of observations.

Skewness, or the third moment, is defined as:

$$Skewness = \frac{\sqrt{N(N-1)}}{N-2} \frac{\sum_{i=1}^{N} \frac{(Y_i - \bar{Y})^3}{N}}{s^3} \tag{3.3}$$

The first term is an adjustment for sample size where the adjustment becomes equal to one with a large sample size. According to Heckert and Filliben (2003), the term becomes 1.02 with N equal to 100. A negative skewness value indicates that the data is skewed toward the left, and a positive value means it is skewed towards the right.

The fourth moment of the distribution is kurtosis, defined as:

$$Kurtosis = \frac{\sum_{i=1}^{N} \frac{(Y_i - \bar{Y})^4}{N}}{s^4} - 3 \tag{3.4}$$

Kurtosis measures the peakiness of the data in excess of three, where a kurtosis value of three is found in a normal distribution. Values above three indicate positive excess kurtosis and the existence of a higher-than-normal number of outliers in the data, with values below three indicating the opposite (Heckert & Filliben, 2003).

The CAPM model assumes that the returns of assets are normally distributed over time. Although it is not necessarily the case that the data used to calculate CAPM is normally distributed. It is more likely to be affected by the higher moments of skewness and kurtosis, which can affect the estimation of the models, as stated by Chang et al. (2013). They argue that the skewness constitutes a risk premium, which also is proposed by Harvey and Siddique (2000).

3.2.2 Return-series

The data used in asset pricing models is typically on return form, which is the case for the CAPM and FF3 models. Therefore, all stock data is differentiated to depict monthly percentage returns. This is done arithmetically, as shown in Equation 3.5 below.

When calculating returns, there is a choice between arithmetic and logarithmic returns. In this thesis, arithmetic returns are used to calculate the returns series, though both returns could be used and compared. But to do so would require a significant increase in the number of regressions needed in the analysis.

$$AR_t = \left(\frac{adjclose_t}{adjclose_{t-1}}\right) - 1, \text{where t } = 1,2,..,\text{T}. \tag{3.5}$$

In the formula AR_t is the arithmetic return of an asset at time t, and $adjclose_t$ refers to the raw adjusted close data from Yahoo Finance, where the current period is divided by the previous period to find the monthly percentage return. This procedure was done for all data used in the asset pricing models that were not prepared beforehand, meaning the FF3 factors were left as is since they came differentiated.

3.2.3 Portfolio Weighting

Market capitalisation data was only collected for the eleven REIT stocks, given the aforementioned issue of data availability and the need to manually collect the data being too time-consuming to be done for all the individual stocks used in the thesis. As a result, the weighting is only done for the REIT data. However, I additionally tried proxying the market cap for the rest of the sectors by using the inverse volatility as a weight, assuming that larger companies were less volatile. The issue was that some years in the data were affected by the reverse relationship, which influenced the results in unwanted ways during estimation.

Equal- and value-weighted portfolios are created using Equations 3.6 and 3.7 below, where the equal-weighted portfolio is created by averaging over all the stock returns in each period in the following way:

$$EW\ portfolio = \left(\frac{r_{1t} + r_{2t} +, \dots, r_{nt}}{n}\right), \text{where t } = \text{ 1,2,..,T.} \tag{3.6}$$

Each return value is added up and then divided by the number of stocks for every month in the dataset. This weighting does not consider anything other than the return value itself. Meaning that, regardless of company size, each company is weighted equally.

The value-weighted portfolio assumes that the market cap data is constant for each month each year since the data only was available at a yearly frequency. Therefore, the weights are created by summing up the total market cap in each period and dividing the individual market cap by the total in each month. The value-weighted portfolio is then created using the weights and returns in the following way:

$$VW\ portfolio = \left(\frac{r_{1t} * w_{1t} + r_{2t} * w_{2t} +, \dots, r_{nt} * w_{nt}}{w_{1t} + w_{2t} +, \dots, w_{nt}}\right), where\ t = 1,2, \dots, T. \qquad (3.7)$$

This then gives the average weighted return for each monthly period, which now considers the "size" of each stock in the portfolio. The reason behind the creation of a value-weighted portfolio is to compare it to the equal-weighted portfolio to correct for potential size bias when equal-weighting.

3.2.4 Leverage Ratio

The leverage ratio is calculated using the debt-to-equity ratio. Similarly to the weighting of portfolios, the data on debt, assets and liabilities were only collected for the REIT data. In the calculation of the D/E-ratio, the yearly values are assumed to be constant for each month in each year. The data is used to estimate the D/E-ratio in the following way:

$$\frac{D}{E} - Ratio_t = \frac{Total\ debt_t}{Total\ assets_t - Total\ liabilities_t}, \text{where t} = 1,2,..,\text{T}. \qquad (3.8)$$

From the equation, an increase in total debt or liabilities will increase the leverage rate, and an increase in total assets will decrease the leverage rate and vice versa.

3.3 Summary Statistics

Table 3.2 below provides the summary statistics for all the stock sectors, including the mean and percentage volatility and the kurtosis and skewness in pure numbers. The table is also split into three separate periods of interest. The full sample period is 2000-2022, and the two subperiods are defined as 2000-2006 and 2010-2022. The GFC period (2007-2009) is avoided in the subperiods in an attempt not to catch the assumed extreme effect it might have had on real estate if included in, for example, a 2000-2009 period.

Two crisis periods are also included in the later analysis, with the Global Financial Crisis being defined within 2007-2009, which is slightly longer than the period defined by NBER but should then catch some of the aftermath of the crisis, which means less spill-over into the bigger subperiods (NBER, 2023). The Covid-19 period is also included from January 2020 to January 2022, but without excluding the period from the 10-22 subperiod as the thesis will attempt not to draw specific conclusions from it but rather use it to explain estimates from those years observed in the rest of the data.

In Table 3.2, the market portfolio (S&P500) generally has lower volatility than the undiversified portfolios, except for consumer staples which, while having higher mean returns, also have lower volatility in all periods. The only other sector showing a similar tendency is REITs during the 00-06 period. A pattern in the table is that the sector with the highest volatility does not have the highest mean returns in most periods, represented by Tech, based on it being outperformed by healthcare and consumer discretionary in two of the three periods.

The mostly negative skewness values in Table 3.2 indicate that the data is skewed towards the left. Most sectors have negative skewness values, though the skewness is not substantially different from 0, meaning the data should have symmetric properties in most cases. Deviations being “other” during the full sample and 10-22 period, and healthcare during the 00-06 period having relatively high skewness values.

Similarly to the skewness values, the “other” sector has high excess kurtosis in the later periods in the data. Similarly, consumer discretionary, healthcare and REIT stocks have high excess kurtosis in different periods. For example, the REIT stock peaked during the 00-22 period, possibly linked to extreme values from the GFC.

Table 3. 2 Descriptive Statistics

Period:		2000-2022		
	Mean	**σ**	**Kurt**	**Skew**
Financials	1,08 %	5,75 %	2,204	-0,547
Healthcare	1,67 %	5,06 %	2,153	0,162
Tech	1,46 %	7,89 %	1,607	0,168
Consumer Disc	1,50 %	6,49 %	3,725	-0,204
Consumer Staples	1,40 %	3,95 %	0,839	-0,136
Industrials	1,49 %	5,65 %	1,552	-0,313
Other	1,20 %	6,95 %	10,748	1,727
REIT	1,05 %	5,82 %	4,435	-0,773
S&P500(Market)	0,33 %	4,49 %	0,760	-0,474

Period:		2000-2006		
Financials	1,43 %	4,09 %	0,840	0,219
Healthcare	2,25 %	5,55 %	3,281	1,244
Tech	1,51 %	10,65 %	0,615	0,333
Consumer Disc	2,01 %	5,94 %	0,732	-0,274
Consumer Staples	1,62 %	2,92 %	0,620	-0,475
Industrials	1,82 %	4,69 %	0,425	-0,471
Other	0,78 %	5,37 %	0,404	0,105
REIT	1,47 %	3,66 %	0,455	-0,539
S&P500(Market)	-0,21 %	4,14 %	0,302	-0,267

Period:		2010-2022		
Financials	1,19 %	5,74 %	1,859	-0,524
Healthcare	1,61 %	4,49 %	0,157	-0,264
Tech	1,64 %	5,85 %	0,267	-0,092
Consumer Disc	1,47 %	5,88 %	4,456	-0,662
Consumer Staples	1,35 %	4,02 %	0,289	0,104
Industrials	1,52 %	5,56 %	1,083	-0,165
Other	1,44 %	6,44 %	14,625	2,009
REIT	1,13 %	5,15 %	2,496	-0,640
S&P500(Market)	0,86 %	4,31 %	0,576	-0,366

Table 3.3 below presents the correlation between all the sectors. The correlations are what would be expected, being over .5 between almost every sector. It gives an inclination of how interconnected the stock market sectors are despite not being diversified. Though none of the sectors are perfectly correlated, an interesting finding is that consumer staples show a similar correlation to the other portfolios and the market portfolio as the other sectors, despite showcasing significantly lower volatility over the full sample period in Table 3.2. The REIT

stocks have the lowest correlation with the market (S&P500), reinforcing the point of higher real estate correlation argued by Hoesli and Oikarinen (2012) put forth in Chapter 2.2; on top of this, it has among the lowest correlation with most of the other sectors. The low correlation with the other parts of the stock market implies that the residential REIT data is influenced less by the stock market's swings. Therefore, given its similarities with the underlying real estate, it will not be as volatile as other stock sectors would be relative to real estate. Including it in a portfolio of the other sectors should then function as a hedge against the risk coming from the market, the implications of which will be covered in Chapter 4.

Table 3. 3 Correlation Table

	Financials	Healthcare	Tech	Consstaples	Consdisc	Industry	Other	REIT	S&P500
Financials	1								
Healthcare	0,583	1							
Tech	0,597	0,739	1						
Consstaples	0,743	0,615	0,602	1					
Consdisc	0,825	0,634	0,737	0,804	1				
Industry	0,838	0,675	0,742	0,797	0,896	1			
Other	0,418	0,369	0,475	0,509	0,446	0,455	1		
REIT	0,656	0,513	0,457	0,618	0,653	0,660	0,331	1	
S&P500	0,702	0,608	0,722	0,674	0,737	0,745	0,548	0,533	1

4 Theory and Methodology

4.1 Theory

4.1.1 Risk

Risk can be split into idiosyncratic and systematic risks. Idiosyncratic risk is risk that affects the individual asset itself, independent of the rest of the market (Hashimzade et al., 2017b). According to Markowitz (1952) portfolio theory, which is the foundation for both asset pricing models, the idiosyncratic risk is assumed to be diversified away. The idea is that assets with low correlation will be good matches in a portfolio, as when one of them goes down in value, a correlation of zero or lower would mean that the other asset was unaffected. Markowitz's theory then advocates that investors choose a portfolio that minimises the risk for a given level of returns through diversification. An example of idiosyncratic risk is the independent capital structure of individual firms. The idea of diversification is mainly based on assumptions such as risk aversion, full information and rationality among investors.

On the other hand, systematic risk is defined as undiversifiable and is, in that sense, the opposite of idiosyncratic risk. When considering stocks, it is the risk connected to the market, where it can be defined as how much the general market influences a stock. This means it is a type of risk that affects the whole market, where it can be compared to a rise in inflation in the sense that it is felt by all economic actors (Hashimzade et al., 2017c). Systematic risk is measured as the beta in the Capital Asset Pricing Model and one of the risk factors in the Fama-French setup.

Critique of the diversification assumption and, in conjunction, the models with roots in it are plentiful. For example, it has been documented that diversification tends to be less prevalent in times of uncertainty or when the investor is directly affected by the risk (Panousi & Papanikolaou, 2012). Articles like the one by Panousi and Papanikolaou (2012) provide evidence that financial managers under-invest and thereby under-diversify when they have direct ownership in the company, something that was believed only could be countered by a higher degree of monetary compensation for the manager (which is a principal-agent issue). Similarly, Goyal and Santa-Clara (2003) find that the return on the market in big part is predicted by average stock variance, being the idiosyncratic risk of the stocks, with the idiosyncratic risk believed to be non-existent in the theory and in the asset pricing models used in this thesis, as it is assumed to be diversified away.

Furthermore, some literature argues that the idiosyncratic risk is not diversified away and exists as a part of the error term when using REIT data in the CAPM framework (Ooi et al., 2009). It is argued by Xu and Malkiel (2004) that this result is general for the overall market, even when Fama-French value and size factors are included. The existence of the idiosyncratic risk is believed to be based on individuals not holding the market portfolio or rather that the investors in the market do not perfectly diversify as they should, according to the CAPM theory. To account for the issue of idiosyncratic risk, some of the literature proposes the inclusion of an idiosyncratic risk premium in the framework, which would be calculated using the residuals of a CAPM regression. However, such an approach would, to the same extent as the other factors, be subject to uncertainty.

4.1.2 Stationarity and Autocorrelation

Stock data is argued to follow the efficient market hypothesis (EMH) by Fama (1970). This implies that the data is non-stationary and has a unit root, where the variance and mean change randomly. This, in turn, makes it hard to predict patterns in the data, which would mean that one could not consistently predict tomorrow’s stock price based on today’s news. If the EMH holds, the stock data follows what is referred to as a random walk, which is unpredictable and will give spurious results in regression analysis. Therefore, the absence of patterns and trends in stock data is central in the EMH.

Since the CAPM and FF3 models use return series, meaning the difference in close price data from one point in time to the next, the non-predictability should be eliminated. The Augmented Dickey-Fuller (ADF) test available in statistical software, which is an extension of the original by Dickey and Fuller (1979) with the augmented version covered in Cheung and Lai (1995), is utilised to check if taking the difference removed the unit root and made the series stationary. The implications are that it is easier to interpret patterns and predict outcomes with constant mean and variance. The series is referred to as I(1) after having taken the first difference; if the data still follows a random walk after differentiating, the second difference can be taken, I(2), and checked using the ADF test.

The results of the ADF test are presented in Appendix A. All the financial return series exhibited stationarity, with the null hypothesis being non-stationarity and a unit root equal to 1. This is the case for all the GICS sectors included in the data.

In addition to the issue of non-stationarity, financial data can exhibit autocorrelation, which arises when the lagged return of a variable predicts its own returns in the next period. If the asset shows high degrees of autocorrelation, usually checked by using the residuals of a regression in a regression on the outcome variable, then it can be used to predict price movements based on its own momentum. To test for autocorrelation, the most common test is the Durbin-Watson test by Durbin and Watson (1951), available in statistical software, which can be applied directly to the regression. The DW statistic ranges between 0 and 4, where a score of 2 means zero autocorrelation, based on degrees of freedom and a DW table. As all the stock return series have higher DW stats than 2, a higher bound must be defined. This is found by taking the lower bound found in the DW table and subtracting it from the number 4. Using this, the cut-off can be set, where any value above can be coined as having significant degrees of, in this case, negative autocorrelation. The results are presented in Appendix A. Generally, some of the stocks are lying around the defined cut-off, so it can be argued that there exists a low level of negative autocorrelation in some of the stock data.

4.1.3 Leverage

Since the betas are calculated based on publicly available data, they will be influenced by the capital structure of the underlying firms. Beta values will then be different relative to the scenario where the underlying firm is entirely equity financed, and they will also be different across the firms (stocks) used in regressions and portfolios.

According to Modigliani and Miller (1958), it is argued that returns increase linearly with a firm's leverage. So therefore, firm value is not decided by capital structure, only by the value of the projects they undertake. This argument will hold according to the theory if the assumption of perfect financial markets is upheld. Central in that assumption by Modigliani & Miller are the assumptions of no taxes, distress, bankruptcy or transaction costs and no asymmetric information. However, the assumption of perfect capital markets does not necessarily reflect the true state of the real world. The true effect of leverage is more complex than simply increasing the expected return on an investment. For example, Andrade and Kaplan (1998) estimate the cost of financial distress to be between 10 to 20 % of firm value, Frank and Goyal (2008) also highlight the impact of transaction and bankruptcy costs in the choice of capital structure and the impact of tax shields making debt more popular than equity financing. These findings advocate what is known as the trade-off theory and highlight the shortcoming of some of the assumptions put forth by Modigliani & Miller, particularly the assumptions of no distress, bankruptcy and transactions cost, and the assumption of no taxes.

4.2 Asset Pricing Methodology

The asset pricing models are defined in this chapter, where of specific importance is the definition of the sectors, as they are made into undiversified portfolios through averaging across firms in every period. They will, for that reason, be referred to as portfolios in the asset pricing frameworks. The methodology and theory presented in this chapter will mainly be based on Fama and French (2004).

4.2.1 Capital Asset Pricing Model – CAPM

The model is based on the portfolio choice model by Markowitz (1952), with investors assumed to be risk averse, while seeking the mean-variance efficient portfolio. Referring to the portfolio that minimises variance given returns and maximises expected returns given variance. Differences in expected returns between assets is then entirely explained by differences in market risk. Two of the main assumptions added by Sharpe (1964) and Lintner (1965) are, firstly, one-period investment perspectives and secondly, unlimited borrowing and lending at the risk-free rate (Fama & French, 2004).

The traditional CAPM presents expected returns of an asset[10] i as:

$$E(R_{it}) = R_t^f + \beta_{im}\left(E(R_t^m) - R_t^f\right) \tag{4.1}$$

In the equation $E(R_{it})$ is the expected return on asset i, R_t^f is the risk-free rate proxied by 1-month T-bills, $E(R_t^m)$ is the expected market return proxied by the S&P500 and β_{im} is the market beta, which measures the systematic risk of the asset. The market beta is formally defined as the covariance of the returns on the asset and the returns on the market, divided by the variance of the return on the market.:

$$\beta_{im} = \frac{cov(R_i, R^m)}{var(R^m)} \tag{4.2}$$

Equation 4.2 implies that stocks highly correlated with the market have higher betas and require a higher rate of return, meaning the beta increases the higher the investment in the asset. The beta can be estimated by regressing the excess return on the asset on the previously defined market risk premium $\beta_{im}\left(E(R_t^m) - R_t^f\right)$ using an OLS[11] approach on the time-series data:

$$R_{it} - R_t^f = \alpha_i \ + \beta_{im}\left(R_t^m - R_t^f\right) + \epsilon_{it} \tag{4.3}$$

The implication of Equation 4.3 is that the expected value of the assets excess return $R_{it} - R_t^f$ is entirely explained by the CAPM risk premium $\beta_{im}\left(R_t^m - R_t^f\right)$. Meaning that the intercept referred to as “Jensen’s alpha”[12] is zero for each asset used in the time-series regression (Fama & French, 2004):

$$\alpha_i = R_{it} - R_t^f - \beta_{im}\left(R_t^m - R_t^f\right) - \epsilon_{it} = 0 \tag{4.4}$$

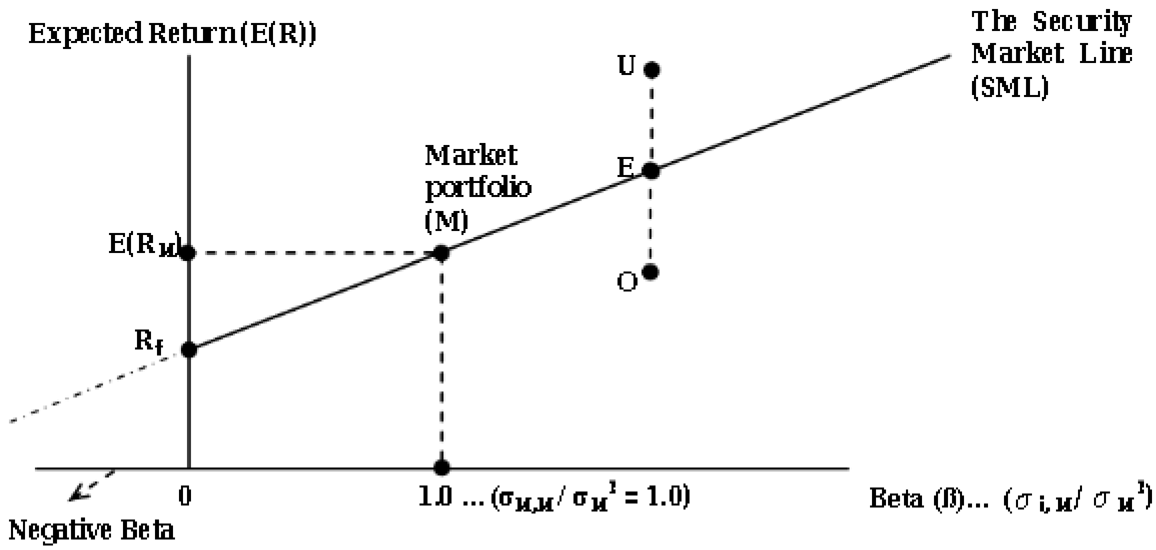
The market risk premium defined as $\left(E(R_t^m) - R_t^f\right)$ in Equations 4.1 and 4.3 represents the difference between investing in the market and the risk-free rate. Or rather, what you could earn on average if you invest your money in a broad market index relative to what you could earn if you invest your money in government bonds. The β_{im} measures market risk, with a

[10] Note that the use of the model is on sector-specific portfolios, which are not individual assets, but will have the same interpretation.
[11] OLS or ordinary least squares regression is the default in asset pricing and is used to estimate betas measuring risk.
[12] Jensen’s alpha is a measure of average return above or below what is predicted by the CAPM model. It is typically used as a measure of fund managers ability to beat the market.

beta equal to 1 indicating that the asset moves jointly with the overall market. In contrast, a beta smaller than 1 means the asset moves less than the market and vice-versa. The beta can also be negative, which means that when the market goes up, the asset goes down and opposite. The alpha, known as Jensen's alpha, represents negative or positive excess returns that the model did not predict (Fama & French, 2004). The variables are, as mentioned in the data chapter, proxied by the S&P500 (R_t^m) and 1-month T-bills (R_t^f).

Given the estimated variables, the formula for expected returns in Equation 4.1 can be used to draw the Security Market Line (SML). The line can be used to evaluate asset risk-return relationships, with higher risk requiring higher returns. This is illustrated in Figure 1 below, with the figure taken from Hodnett and Hsieh (2012). When we move along the x-axis and beta becomes higher, the expected returns, or rather, the compensation for the increased risk, goes up along the y-axis. If a stock estimated through the CAPM model has actual returns over or under the SML, then the stock is over- or undervalued relative to the expected risk-return relationship precited by the CAPM model.

Figure 4. 1 The Security Market Line



Note: The figure depicts the security market line from Hodnett and Hsieh (2012).

Though the CAPM model often comes under scrutiny, it is rather simple to use while providing results that show somewhat expected and easy-to-interpret patterns. The model itself relies on assumptions such as no transaction costs, no taxes, one-period investment horizons for investors, and homogenous expectations about asset returns (Berk & DeMarzo, 2017). It further assumes that investors are rational and risk averse and that they seek the portfolio with the lowest beta for a given level of returns, and that they can borrow and lend money at the risk-free rate (Hashimzade et al., 2017a), often assumed to be 1–10-month treasury bills. The model assumes a linear relationship between the risk measured by the CAPM beta and the expected returns, where higher risk constitutes higher returns and vice-versa (Fama & French, 2004).

4.3.2 Fama-French Model

The model proposed by Fama and French (1992) was devised as, in essence, an extension of the CAPM model with the goal of improving the understanding of risk and returns with the expected returns in FF3 defined as:

$$E(R_{it}) = R_t^f + \beta_{im}\left(E(R_t^m) - R_t^f\right) + \beta_{is}E(SMB_t) + \beta_{ih}E(HML_t) \tag{4.5}$$

The first addition when we move on from the CAPM model is the SMB_t (small minus big) factor, which is the difference between returns on diversified portfolios of small and big stocks, measured by market capitalisation. The second addition is the HML_t (high minus low) factor, which is the difference between returns on diversified portfolios of high and low B/M stocks (Fama & French, 2004), with the betas estimated using the following multiple regression model:

$$R_{it} - R_t^f = \alpha_i + \beta_{iM}\left(R_t^m - R_t^f\right) + \beta_{is}SMB_t + \beta_{ih}HML_t + \varepsilon_{it} \tag{4.6}$$

The alpha in the FF3 model is assumed to be equal to zero like in the CAPM model (Fama & French, 2004). The new factors are both defined on the Kenneth French data page (French, 2023) in the following way:

$$SMB = \frac{1}{3} * (Small\ Value + Small\ Neutral + Small\ Growth) - \frac{1}{3} * (Big\ Value + Big\ Neutral + Big\ Growth) \tag{4.7}$$

And:

$$HML = \frac{1}{2} * (Small\,Value + Big\,Value) - \frac{1}{2} * (Small\,Growth + Big\,Growth) \quad (4.8)$$

The factors are constructed using six value-weighted portfolios that were created based on book-to-market and size. The SMB is the average return on three small portfolios minus the average return on three big portfolios. The HML factor is the average return on two value[13] portfolios minus the average return on two growth[14] portfolios (French, 2023).

Finally, the model gets extended to include a factor for the underlying housing market, which is found by subtracting the risk-free rate from an estimated return series of the house factor, inspired by Lee et al. (2008). It extends the model to a four-factor model, with the regression becoming:

$$R_{it} - R_t^f = \alpha_i + \beta_{im}\left(R_t^m - R_t^f\right) + \beta_{is}(SMB_t) + \beta_{ih}(HML_t) + \beta_{ir}(RE_t) + \varepsilon_{it} \quad (4.9)$$

The expected returns are being extended in a similar fashion:

$$E(R_{it}) = R_t^f + \beta_{im}\left(E(R_t^m) - R_t^f\right) + \beta_{is}E(SMB_t) + \beta_{ih}E(HML_t) + \beta_{ir}E(RE_t) \quad (4.10)$$

When the beta values are calculated, the D/E – ratio provided in Equation 3.8 can be used to find the unlevered beta values. The formula used is the one proposed by Bernardo et al. (2007):

$$\beta_i^u = \frac{\beta_i^l}{\left[1 + (1-T) * \left(\frac{D}{E} - Ratio\right)\right]} \quad (4.11)$$

The FF models used in the analysis consist of four additional equity betas that will be adjusted following the same process. The superscripts u and l refer to the unlevered and levered beta values, and T is the included tax rate. The REIT dividend tax rate of 29% will be used as the T in Equation 20 based on the tax rate on the NAREIT website and further assumed to be constant during the entire 2000-2022 period (NAREIT, n.d).

[13] Value refers to the stock being what is defined as Value stocks which are stocks trading at a lower price than what would be fundamentally expected.
[14] Growth refers to the stock being what is defined as Growth stocks, which are companies that are anticipated to grow faster than other stocks on the market, they usually don't pay dividends as all returns are reinvested in the growth.

Fama & French refines the idea of risk outlined in the CAPM model by saying that it not only is decided by the correlation with the market measure by the market risk factor but also by size and value risk factors. The size factor is based on the empirical result that smaller companies have higher expected returns than large companies, where the small companies are riskier than the large companies. The value factor is based on the empirical results that high book-to-market companies earn higher returns than companies with low book-to-market (Fama & French, 2004).

4.3.3 Real Estate and the Asset Pricing Models

Empirical work on financial assets tends to utilise both asset pricing models, meaning there will be some overlap in the discussion of the empirical literature when both models are used. Therefore, when talking about the empirical literature using the models on real estate, I will refer to the study using "asset pricing models" instead of one or the other model.

Usage of the asset pricing models directly on some form of return series for the underlying asset is rare. It can likely be attributed to difficulties surrounding both data availability and access. One study having access to better data is the one by Cannon et al. (2006), who use zip code-level house price data. They examine US MSAs and find that the data follows the expected risk-return trade-off assumed specifically in the CAPM theory. Further, they find that areas with a higher correlation with the stock market see more price growth during economic upturns while also experiencing higher volatility.

Conversely, usage of REIT data is more common in the asset pricing frameworks as the data generally has higher availability. One example is the article by Ro and Ziobrowski (2011), who use REIT industry-specific data to analyse the gains of diversification versus specialisation within the REIT sector. They find no evidence of superior performance in an undiversified REIT portfolio, referring to specialising fund managers not generating above-average returns. Similarly, Lee et al. (2008) examines the link between REITs and the underlying real estate and find that REIT returns reflect the performance of the underlying real estate; they also include a housing factor by lagging the NCREIF index[15]. At the same time, their work revolves around all equity REITs with no specific subsets. Something I argue can hurt the analysis. Simply because REIT data is different across industries, to such an extent that results from one industry have no connection to the results of another. The difference between the underlying real estate in the residential industry relative to the hotel or industrial industries is significant if one considers the type of property each deal in. It can be assumed that there always will be demand for a roof over the head and that this demand for residential real estate will be somewhat constant. Similarly, the hotel sector will be influenced by seasonality and far higher costs as far as depreciation and administration go. If both industries were included under the real estate sector banner, the resulting risk-return relationship would not reflect any of the industries, with the problem reinforced in the usage of all equity REITs in asset pricing. This thesis attempts to examine real estate in asset pricing frameworks while at the same time ensuring that the results reflect the risk and return of the underlying asset as optimally as possible. The goal is to find the most easily accessible real estate investment for retail investors' position in optimal portfolio diversification.

4.3.4 Critique of the Models

The CAPM model implies that investors should divide their funds between the risk-free rate and the market portfolio, because it supplies the minimum risk given a level of return, and no other risky portfolio should be considered (Hashimzade et al., 2017a). Additionally, the model relies upon several assumptions of investors' actions and the market's functioning. Some of these assumptions have been challenged and deemed unrealistic or wrong, which means that the empirical fundament of the CAPM model does not necessarily hold. As stated by Fama and French (2004), it is generally unrealistic to assume unlimited borrowing and lending. The idea that investors only care about risk-return trade-offs over single-period horizons does not hold either, simply because it can be expected that they also consider labour income, labour costs, and future investment possibilities, not just investments today. In addition, the predicted linear relationship between beta and the expected return has been proven to be "too flat", questioning the validity of the assumed relationship. The constant term referred to as Jensen's alpha has consistently been estimated to be bigger than the risk-free rate. Estimating the returns of a portfolio against the market to measure abnormal returns, the CAPM model

[15] NCREIF refers to the National Council of Real Estate Investment Fiduciaries, which provides an in-depth real estate sales index.

predicts abnormal returns for portfolios that are passively managed, meaning that fund managers are predicted to do better than they actually do, based on the assumption of Jensen's alpha being zero (Fama & French, 2004).

While the FF3 model is created upon the critique and empirical testing of the CAPM model, it has not gone without critique itself. Bernardo et al. (2007) point out that a problem with the usage of the FF3 model is the determination of the cost of capital, referring to the effect leverage has on risk and returns because the factor loadings (SMB & HML) are unstable over time. Furthermore, there is discussion upon the validity of specifically the value factor HML: Black (1993) points out, among other things, the issues of data mining in creating the factor and the lack of relevance in the size of companies explaining expected returns. Other arguments, like the one by MacKinlay (1995), argue that multifactor models like the FF3 don't explain the deviations from the assumptions in the CAPM model either. Though while there always will exist more critique of both models, see Kothari et al. (1995) and Daniel and Titman (1997), it is such that the CAPM and FF3 models still are actively used in asset pricing and finance today, meaning their relevance and empirical power cannot be understated.

5 Analysis

5.1 Levered REIT Regressions

Before conducting the regression analysis, I examine the correlation between the two housing indices and the REIT return series. Based on the correlations in Table 5.1 below, the MSA index is selected for inclusion in the FF4 model as it showed higher contemporaneous and lagged correlation. A two-month lag of the REIT data gave the highest correlation when checking both house price indices, which will be because stock returns depend on the past performance of the underlying market, but not with more lag than two months. The literature generally finds that REIT stocks have a lower correlation with the house-price indices than the stock market. Therefore, propositions such as the one by Giliberto (1993) have been made to correct the low correlation, where it is increased by hedging the correlation that is connected to the stock market. Though the method only provides marginal gains. And with arguments such as the one by Hoesli and Oikarinen (2012), it can be assumed that there is a higher long-term correlation between the underlying real estate and REIT stocks.

Table 5. 1 Real Estate Index Correlation

No lag	***MSA-index***	***FHFA-Index***	***REIT Portfolio***
MSA-Index	1		
FHFA-Index	0,708106729	1	
REIT Portfolio	0,157616518	0,086343072	1

2-Month lag	***MSA-Index***	***FHFA-Index***	***REIT Portfolio***
MSA-Index	1		
FHFA-Index	0,708106729	1	
REIT Portfolio	0,236676867	0,188776021	1

The first section of the analysis will focus on the REIT equity betas, estimated using the asset pricing models presented in Chapter 4. Equity beta refers to the levered beta of an asset, as the capital structure of the firm will influence its size, where based on Modigliani and Miller

(1958), the beta is assumed to increase with the leverage, and the returns increase with the beta.

Tables 5.2 and 5.3 below present the estimated CAPM, FF3, and FF4 betas. The regressions are done on the full sample period from 00-22 and the previously mentioned subsets of 00-06 and 10-22 in Table 5.2. With the addition of the subsets of the GFC (07-09) and Covid-19 (01.20-01.22) in Table 5.3.

While most periods are defined by betas around $0.2 - 0.7$, as observed in Table 5.2. What stands out is the GFC, as it is characterised by significant and high risk in the REIT sector with betas higher than 1. While when looking at Table 5.4, provided further down in the chapter, the expected monthly returns corresponding to the betas of the GFC are negative. This is a period where the assumptions of the CAPM model fall short as an inverse risk-return relationship is apparent. The reason behind this relationship can be attributed to high leverage ratios among REITs leading up to the period, as pointed out by Sun et al. (2015). Though it also will be caused by the expected returns of the market and risk factors during the period being negative. When comparing the asset pricing models, there is no large difference between market risk estimates using CAPM and FF3. Though most of the periods in Tables 5.2 and 5.3 see a reduction in the market risk beta as the additional factors capture more of the unobserved risk[16] otherwise captured by the market beta or through the residuals.

What is noteworthy in Tables 5.2 and 5.3 is the differences in estimated betas before and after the GFC, with the market risk being low at around .223-.350 from 00-06, rising to around .592-.530 from 10-22 across both models. Additionally, the SMB and HML factors lost significance in periods after the GFC, implicating two things. First, the market risk of the full sample is highly influenced by the years after 2006, with market risk betas also being high during Covid-19 likely being a cause. Secondly, the FF3 factors losing significance in later periods implicates stronger explanatory power of the market risk premium following the GFC,

[16] Note that this only is the case when the additional risk factors are statistically significant, which also is the case for the rest of the regressions in the analysis.

meaning the FF3 risk factors do not contribute to explaining risk-return relationships from 2010 and onwards when using REIT stock data.

Lastly, an important point reiterated throughout this chapter is that standard errors remain relatively constant while the estimated betas vary significantly across periods. Where the issue is most clear in the periods with a smaller number of observations and when using the CAPM model. With the standard errors being smaller in the estimated 00-06 period than they are in the full sample and the 10-22 period. This discrepancy suggests potential flaws in the estimation process when utilising real estate data and might be caused by both flaws in model assumptions and assumptions about the data distribution when employing statistical software.

Table 5. 2 Levered REIT betas

Period:			**2000-2022**			
	(1)	(2)	(3)	(4)	(5)	(6)
Weight:	***EW***	***VW***	***EW***	***VW***	***EW***	***VW***
S&P500	0.690***	0.700***	0.631***	0.653***	0.625***	0.593***
	(0.102)	(0.0998)	(0.0829)	(0.0816)	(0.0826)	(0.0767)
SMB			0.373***	0.269***	0.371***	0.324***
			(0.0906)	(0.0981)	(0.0910)	(0.0860)
HML			0.483***	0.493***	0.475***	0.418***
			(0.103)	(0.107)	(0.103)	(0.0998)
MSA					0.273	0.332
					(0.426)	(0.394)
a	0.0087***	0.0083**	0.0072**	0.0068**	0.00611**	0.00489*
	(0.00314)	(0.00323)	(0.00303)	(0.00309)	(0.00292)	(0.00274)
n	276	276	276	276	276	276
R-squared	0.270	0.265	0.340	0.335	0.341	0.336
Period:			**2000-2006**			
S&P500	0.223**	0.338***	0.350***	0.488***	0.350***	0.332***
	(0.0921)	(0.118)	(0.0823)	(0.111)	(0.0825)	(0.0786)
SMB			0.335***	0.275**	0.335***	0.317***
			(0.101)	(0.112)	(0.101)	(0.0958)
HML			0.488***	0.564***	0.487***	0.453***
			(0.140)	(0.150)	(0.137)	(0.131)
MSA					-0.0620	0.0441
					(0.753)	(0.704)
a	0.016***	0.017***	0.0088*	0.0094*	0.00823*	0.00773*
	(0.00433)	(0.00477)	(0.00489)	(0.00523)	(0.00440)	(0.00412)
n	84	84	84	84	84	84
R-squared	0.076	0.097	0.204	0.215	0.206	0.217
Period:			**2010-2022**			
S&P500	0.592***	0.581***	0.530***	0.535***	0.529***	0.0159
	(0.119)	(0.120)	(0.109)	(0.111)	(0.110)	(0.121)
SMB			0.300*	0.224	0.305*	-0.133
			(0.168)	(0.188)	(0.169)	(0.200)
HML			0.108	0.0758	0.119	-0.109
			(0.163)	(0.159)	(0.164)	(0.157)
MSA					0.0287	0.813
					(0.647)	(0.622)
a	0.0064	0.0055	0.0067*	0.0058	0.00679*	0.00659
	(0.00402)	(0.00405)	(0.00397)	(0.00401)	(0.00401)	(0.00632)
n	156	156	156	156	156	156
R-squared	0.231	0.230	0.235	0.235	0.235	0.235

*Note: The significance level is denoted by *, with *** being a significance level of 1%.*

Regressions: CAPM: $R_{it} - R_t^f = \alpha_i + \beta_{im}(R_t^m - R_t^f) + \epsilon_{it}$. *FF3:* $R_{it} - R_t^f = \alpha_i + \beta_{im}(R_t^m - R_t^f) + \beta_{is}(SMB_t) + \beta_{ih}(HML_t) + \beta_{ir}(RE_t) + \varepsilon_{it}$.

Table 5. 3 *Levered REIT beta Estimate - Subperiods*

Period:	**GFC (07-09)**					
Weight:	***EW***	***VW***	***EW***	***VW***	***EW***	***VW***
S&P500	1.538***	1.484***	1.153***	1.067***	1.110***	1.051***
	(0.183)	(0.199)	(0.130)	(0.148)	(0.143)	(0.153)
SMB			0.808***	0.427	0.824***	0.433
			(0.282)	(0.334)	(0.264)	(0.339)
HML			0.986***	1.256***	1.081***	1.290***
			(0.351)	(0.292)	(0.288)	(0.261)
MSA					1.935	0.715
					(1.559)	(1.634)
n	48	48	48	48	48	48
R-squared	0.589	0.549	0.764	0.730	0.772	0.737
Period:	**Covid-19 (2020.2022)**					
S&P500	0.786**	0.787***	0.692**	0.710***	0.693***	0.711***
	(0.304)	(0.280)	(0.250)	(0.236)	(0.241)	(0.234)
SMB			0.108	0.0364	0.178	0.101
			(0.424)	(0.414)	(0.403)	(0.396)
HML			0.273	0.267	0.113	0.119
			(0.296)	(0.268)	(0.278)	(0.264)
MSA					3.763*	3.483
					(2.041)	(2.055)
n	25	25	25	25	25	25
R-squared	0.404	0.413	0.427	0.441	0.475	0.489

Note: Table 5.3 extends Table 5.2 with the crisis periods defined as the Great Financial Crisis from 2007-2009 and Covid-19 from 2020-2022.

In Table 5.4, presented below, the expected returns are calculated using the estimated betas based on the equation provided in Chapter 4. The expected returns demonstrate a pattern where the CAPM model consistently predicts lower expected returns compared to the FF3 model. Specifically in the periods where the SMB and HML factors are statistically significant in Tables 5.2 and 5.3. The assumed linear relationship between risk and return is evident in all periods except for the GFC (as discussed previously), with lower risk resulting in lower returns and vice-versa. The reason behind the negative returns during the crisis is explained by the highly negative expected returns of the variables included in the CAPM and FF3 formulas. For instance, during the GFC period, the expected return on the S&P500 was strongly negative at -0.5% monthly, and the expected HML factor was at -0.49% monthly, which is why the returns become negative.

Table 5. 4 *Levered Expected REIT Returns*

Period:	**2000-2022**		**2000-2006**		**2010-2022**	
Weight:	***EW***	***VW***	***EW***	***VW***	***EW***	***VW***
CAPM	0,355 %	0,358 %	0,203 %	0,180 %	0,553 %	0,544 %
FF 3-Factor	0,529 %	0,519 %	0,911 %	0,914 %	0,497 %	0,502 %
FF 4-Factor	0,596 %	0,578 %	0,888 %	0,881 %	0,508 %	0,408 %
Period:	**GFC**				**Covid-19**	
Weight:	***EW***	***VW***			***EW***	***VW***
CAPM	-0,861 %	-0,825 %			0,971 %	0,973 %
FF 3-Factor	-0,958 %	-1,093 %			0,869 %	0,881 %
FF 4-Factor	-1,002 %	-1,006 %			4,853 %	-0,966 %

Note: The table presents the expected returns calculated using the estimated betas from Tables 5.2 and 5.3 in the CAPM formula for expected returns on the form:
$E(R_{it}) = R_t^f + \beta_{im}\left(E(R_t^m) - R_t^f\right)$ *and FF3 formula for expected returns on the form:* $E(R_{it}) = R_t^f + \left(E(R_t^m) - R_t^f\right) + \beta_{is}E(SMB_t) + \beta_{ih}E(HML_t)$.

Based on the results of the levered analysis, it seems that the weighting of the portfolios has little impact on the determination of betas, with results varying in no clear direction depending on the weighting. However, it appears to have a negative effect on the explanatory power of the SMB factor in the 00-06 and GFC periods. This suggests that value-weighted portfolios may be excluded from further analysis while the FF3 model is utilised. Additionally, the housing factor will also be excluded as it did not improve the explanatory power of the models, likely because it is based on sales income and not rental income from real estate.

5.2 Unlevered REIT Results

To estimate unlevered betas, I used the collected debt and equity data, weighted similarly to the value-weighted portfolio, by utilising market capitalisations. The reason for examining the effect of leverage is that the data obtained from Yahoo Finance will estimate the equity beta as it is not corrected for the firm's capital structure. According to Modigliani and Miller (1958), the betas should be higher given a more leveraged capital structure, and the higher betas should be compensated with higher expected returns. As mentioned earlier, the data used to account for the leverage has a yearly frequency and is assumed constant for each monthly observation. Implying that the statistical inference that can be drawn from the results of removing leverage must be taken with a grain of salt while they will still indicate the impact of leverage on the risk of the asset. It will be assumed that periods of high leverage among REITs, defined as the periods before 2010 according to Sun et al. (2015) and Mattson-Teig (2020), see sizeable reductions in risk and expected return as an effect of removing leverage. The results of removing leverage from the betas are presented in Table 5.5 below, with standard errors and significance levels remaining unchanged compared to Tables 5.2 and 5.3 since the models have not been re-estimated using a new regression. The reason being that they simply have been adjusted using the formula presented in Bernardo et al. (2007). The table also displays the percentage change in risk moving from levered to unlevered beta to highlight the percentage of real estate risk that can be attributed to leverage.

The size of the leverage risk is biggest during the GFC, with the market risk reduced by 68% in both the CAPM and FF3 models. The market risk is generally reduced by between $43\% - 51\%$ in the other periods meaning the leverage of REITs increased their market risk by roughly 50%, with the FF3 factor loadings showing a similar pattern. Additionally, given the reduced explanatory power of the SMB and HML factors from 2010 and onwards, the unlevered expected returns for the post-GFC periods will not be statistically significant either and, therefore, only provide an inclination of their effect on expected returns.

With the expected returns estimated using the unlevered betas presented in Table 5.6. The relationship between leverage, risk, and expected returns from the Modigliani and Miller (1958) theory holds for all the periods except for the GFC and the anomaly that is the 00-06 CAPM model estimate. The theory breaks similarly to the CAPM model during the GFC as the leverage leads to increased negative expected returns, with the underlying reasoning being unchanged from the one in Chapter 5.1. The size of the losses given the leverage is estimated to be about 0.7% monthly for both the CAPM and FF3 models, meaning leverage plays a significant role in the risk and losses of residential REITs during the GFC. Where the issue of the 00-06 CAPM regression possibly is caused by fundamental issues with the data and the assumptions surrounding it. As the implication of the positive expected returns and generally low market betas being that the six-year period is very stable compared to the rest of the data. While also being seemingly unaffected by capital structure based on the positive expected returns.

Table 5. 5 *Unlevered Beta Estimates*

Period:		**2000-2022**		
Unlevered portfolio:	***EW***	**% Change**	***EW***	**% Change**
S&P500	0.336	-51 %	0.307	-51 %
SMB			0.182	-51 %
HML			0.235	-51 %
n	276		276	
Period:		**2000-2006**		
S&P500	0.109	-51 %	0.171	-51 %
SMB			0.163	-53 %
HML			0.238	-51 %
n	84		84	
Period:		**2010-2022**		
S&P500	0.328	-45 %	0.294	-45 %
SMB			0.166	-45 %
HML			0.06	-44 %
n	156		156	
Period:		**GFC**		
S&P500	0.490	-68 %	0.367	-68 %
SMB			0.257	32 %
HML			0.314	-68 %
n	48		48	
Period:		**Covid-19**		
S&P500	0.450	-43 %	0.396	-50 %
SMB			0.062	-91 %
HML			0.156	-43 %
n	25		25	

Note: Table 5.5 presents the unlevered betas calculated using the method by Bernardo et al. (2007), including a measure of the percentage change in risk from the levered to the unlevered beta.

Table 5. 6 *Unlevered Expected REIT Returns*

Period:	**2000-2022**		**2000-2006**		**2010-2022**	
Portfolio:	***EW***	**% diff**	***EW***	***% diff***	***EW***	***% diff***
CAPM	0,236 %	-0,118 %	0,227 %	0,024 %	0,327 %	-0,226 %
FF 3-Factor	0,321 %	-0,208 %	0,572 %	-0,339 %	0,296 %	-0,201 %
Period:	**GFC**				**Covid-19**	
Portfolio:	***EW***	***% diff***			***EW***	***% diff***
CAPM	-0,156 %	0,705 %			0,565 %	-0,407 %
FF 3-Factor	-0,187 %	0,771 %			0,506 %	-0,363 %

Note: Table 5.6 reports the expected returns of the models after controlling the equity betas for leverage, the same formula for expected returns is used as in Table 5.4.

From the analysis of leverage, it is pointed out that the risk of the asset increases with the leverage, meaning the risk of the asset will be split in two, one part being the risk from the asset itself and the other being the risk associated with the leverage of the asset. Given the linear relationship between risk and return predicted by CAPM and Modigliani & Miller, the increased market risk should lead to higher expected returns. Thus, while the FF3 predicts a more multivariate view, the idea of higher risk relating to higher returns still stands for the additional variables, as shown in Tables 5.5 and 5.6. While the effect of rare events such as the GFC poses a challenge when estimating the risk of leverage and risk in general. Since the inverse relationship between risk and expected returns and leverage and expected returns can't be compared to similar rare events such as the 1990 recession. The GFC then cannot be analysed considering other factors beyond the assumptions made by the model and the data at hand. Consequently, drawing larger conclusions based on the results from the period becomes challenging, except for noting the evident discrepancies in estimated values compared to other periods of interest included in the data.

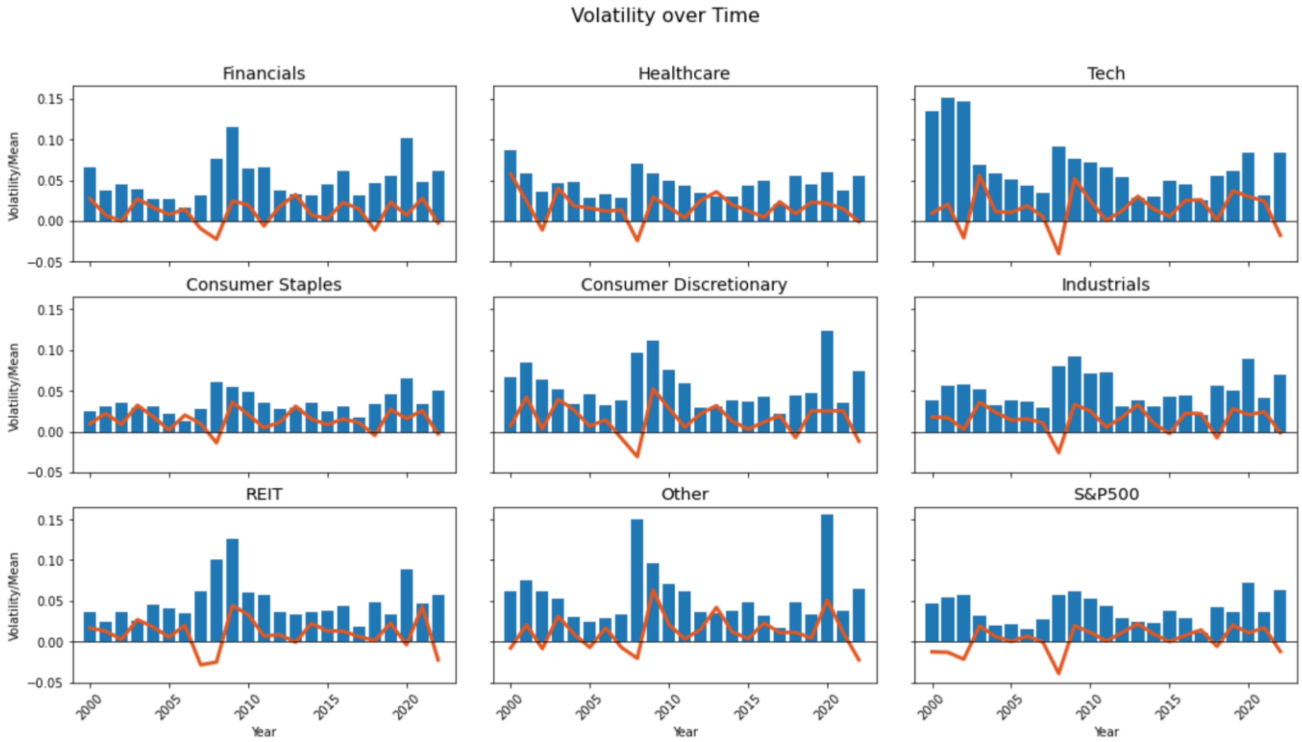
5.3 Sector-specific Risk

To find the position of real estate in an optimal portfolio, the analysis is extended to include all the GICS sectors. The historical return-volatility relationship of all nine portfolios, including the S&P500, is presented in Figure 5.1 below, with the pillars representing the average annual volatility and the line representing the average annual returns. The figure shows that the healthcare, consumer staples and S&P500 portfolios exhibit the lowest volatility over the entire period. This is demonstrated by the relatively lower fluctuations in the volatility of these portfolios. This lower volatility may be attributed to the inelastic demand[17] for products the undiversified sectors supply. In comparison, a sector like consumer discretionary, which is more elastic, is more susceptible to the effects of a recession such as the one during 2007-2009, based on the figure. Furthermore, the S&P500, being a diversified portfolio unlike the sector-specific portfolios, displays low relative volatility, which is expected and justifies its inclusion as the market portfolio.

Conversely, the tech and financial sectors have similar volatility to consumer discretionary, with the tech sector having the highest volatility over the full sample period during the years following the dot-com bubble of the early 2000s. The volatility in the financial sector during that period was connected to the volatility of the tech sector through large hedge fund investments; see Griffin et al. (2011) and Brunnermeier and Nagel (2004). While the REIT sector and financial sector also follow a similar pattern of volatility during the GFC, which can be attributed to the interconnected risk of banking and real estate, and the rise of mortgage-backed-securities during the early 2000s, see Brunnermeier (2009) and Levitin and Wachter (2011).

[17] Inelastic demand refers to the good having static demand even though the price goes up.

Figure 5. 1 *Sector Specific Volatility & Returns*



From Figure 5.1, it is clear that the GFC had a strong influence on the REIT sector. However, given the data not going further back than the year 2000, the scope of the analysis gets limited, as previously mentioned. As a result, the impact of a rare event like the GFC becomes harder to pinpoint, and results become more ambiguous. The reason is that even though a rare event is rare, it can be severe. For example, if these events occur once every 20 years and sector returns are reduced by a significantly big relative amount each time, then most investors would not hold the most influenced sectors in their portfolios.

The regressions using the sector data are reported in Tables 5.7, 5.8 and 5.9 below, with the CAPM results presented in Table 5.7 and FF3 results presented in Tables 5.8 and 5.9. Notably, the sectors displaying high volatility in Figure 5.1 also exhibit high levels of market[18] risk in all the estimated periods of Tables 5.7, 5.8 and 5.9, namely the financial, tech, consumer discretionary, industrials and "other" sectors. On the other hand, REIT stocks generally demonstrate low systematic risk in all periods except during the GFC. Based on the CAPM assumptions, the high-risk stocks should be compensated for the higher risk, but the

[18] Referring to systematic risk, whereas volatility consists of both systematic and diversifiable risk, so high volatility does not necessarily equal high systematic risk.

CAPM model might fall short as it did with only the weighted REIT portfolios. Making the optimal portfolio harder to identify and evaluate.

The high market risk of the tech portfolio in every regression can be attributed to the significant representation of tech stocks in the later parts of the data period[19]. This raises the question of whether the S&P500 is an appropriate proxy for the market when analysing tech stocks. In contrast, the healthcare sector holds the second largest weight in the S&P500 despite being in the lower sight when looking at the betas. Additionally, based on the correlations provided in Chapter 3, Table 3.3, tech did not have the highest correlation with the S&P500 among the sectors. The reason behind this discrepancy could instead stem from the HML factor being strongly negative and significant in column 4 of Tables 5.8 and 5.9, reflecting the influence of growth stocks outperforming value stocks in the tech sector.

[19] Based on the weighting of the portfolio provided by Yahoo Finance. (2023). *SPDR S&P 500 ETF Trust (SPY)*. Yahoo Finance. https://finance.yahoo.com/quote/SPY/holdings/.

Table 5. 7 *Sector CAPM Betas*

Period:				**2000-2022**				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Index:	**REIT**	**Financials**	**Healthcare**	**Tech**	**Cons-Sta**	**Cons-Dis**	**Industry**	**Other**
S&P500	0.692***	0.906***	0.691***	1.275***	0.599***	1.073***	0.944***	0.855***
	(0.102)	(0.0784)	(0.0654)	(0.0922)	(0.0516)	(0.0933)	(0.0726)	(0.0968)
a	0.00828***	0.00671***	0.0133***	0.00936***	0.0109***	0.0104***	0.0107***	0.00815**
	(0.00304)	(0.00251)	(0.00244)	(0.00329)	(0.00174)	(0.00263)	(0.00226)	(0.00351)
n	276	276	276	276	276	276	276	276
R-squared	0.284	0.497	0.376	0.524	0.461	0.547	0.560	0.303
Period:				**2000-2006**				
S&P500	0.223**	0.716***	0.686***	2.072***	0.426***	1.092***	0.823***	1.088***
	(0.0921)	(0.0754)	(0.131)	(0.177)	(0.0729)	(0.133)	(0.0971)	(0.0985)
a	0.0152***	0.0133***	0.0214***	0.0169**	0.0146***	0.0198***	0.0174***	0.00755**
	(0.00391)	(0.00307)	(0.00519)	(0.00699)	(0.00255)	(0.00420)	(0.00351)	(0.00324)
n	84	84	84	84	84	84	84	84
R-squared	0.064	0.528	0.263	0.647	0.360	0.576	0.526	0.699
Period:				**2010-2022**				
S&P500	0.593***	0.871***	0.619***	0.890***	0.588***	0.952***	0.891***	0.543***
	(0.120)	(0.124)	(0.0924)	(0.121)	(0.0786)	(0.141)	(0.116)	(0.151)
a	0.00641	0.00437	0.0106***	0.00866**	0.00827***	0.00652*	0.00749**	0.00950*
	(0.00388)	(0.00375)	(0.00302)	(0.00359)	(0.00247)	(0.00361)	(0.00334)	(0.00510)
n	156	156	156	156	156	156	156	156
R-squared	0.244	0.423	0.349	0.426	0.393	0.481	0.472	0.130

*Note: The significance level is denoted by *, with *** being a significance level of 1%. Using the same regressions as in Table 5.2.*

Table 5. 8 *Sector FF3 Betas*

Period:				2000-2022				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Index:	**REIT**	**Financial**	**Healthcare**	**Tech**	**Cons-Sta**	**Cons-Dis**	**Industry**	**Other**
S&P500	0.633***	0.853***	0.622***	1.203***	0.563***	1.005***	0.883***	0.812***
	(0.0832)	(0.0563)	(0.0654)	(0.0947)	(0.0475)	(0.0788)	(0.0608)	(0.0937)
SMB	0.373***	0.247***	0.612***	0.710***	0.237***	0.454***	0.415***	0.345***
	(0.0904)	(0.0649)	(0.107)	(0.147)	(0.0604)	(0.117)	(0.0822)	(0.125)
HML	0.485***	0.746***	-0.105	-0.354***	0.260***	0.451***	0.395***	0.0972
	(0.102)	(0.0727)	(0.0713)	(0.100)	(0.0562)	(0.0933)	(0.0686)	(0.155)
a	0.00643**	0.00439**	0.0126***	0.00912***	0.00982***	0.00853***	0.00906***	0.00734**
	(0.00287)	(0.00192)	(0.00209)	(0.00282)	(0.00163)	(0.00237)	(0.00200)	(0.00362)
n	276	276	276	276	276	276	276	276
R-squared	0.385	0.695	0.540	0.648	0.532	0.633	0.650	0.326
Period:				**2000-2006**				
S&P500	0.350***	0.887***	0.665***	1.927***	0.554***	1.288***	1.013***	1.151***
	(0.0823)	(0.0558)	(0.109)	(0.136)	(0.0435)	(0.0967)	(0.0607)	(0.0945)
SMB	0.335***	0.0678	0.745***	0.860***	0.296***	0.493***	0.476***	0.379***
	(0.101)	(0.0671)	(0.138)	(0.171)	(0.0662)	(0.126)	(0.0822)	(0.0811)
HML	0.488***	0.617***	0.00695	-0.426***	0.489***	0.751***	0.726***	0.266**
	(0.140)	(0.110)	(0.120)	(0.146)	(0.0623)	(0.141)	(0.0848)	(0.110)
a	0.00808*	0.00635***	0.0172***	0.0166***	0.00771***	0.00907**	0.00699**	0.00260
	(0.00439)	(0.00212)	(0.00395)	(0.00495)	(0.00223)	(0.00441)	(0.00306)	(0.00315)
n	84	84	84	84	84	84	84	84
R-squared	0.222	0.764	0.629	0.859	0.590	0.714	0.733	0.765
Period:				**2010-2022**				
S&P500	0.529***	0.710***	0.561***	0.824***	0.524***	0.835***	0.772***	0.494***
	(0.110)	(0.0953)	(0.0979)	(0.128)	(0.0824)	(0.123)	(0.107)	(0.151)
SMB	0.305*	0.578***	0.442***	0.415***	0.296***	0.535***	0.555***	0.302
	(0.169)	(0.134)	(0.0973)	(0.138)	(0.0980)	(0.132)	(0.138)	(0.220)
HML	0.120	0.640***	-0.197*	-0.0629	0.130	0.254	0.240**	-0.0477
	(0.161)	(0.114)	(0.105)	(0.142)	(0.0848)	(0.161)	(0.119)	(0.230)
a	0.00691*	0.00572*	0.0109***	0.00911**	0.00877***	0.00743**	0.00841***	0.00983*
	(0.00377)	(0.00302)	(0.00286)	(0.00356)	(0.00244)	(0.00321)	(0.00310)	(0.00509)
n	156	156	156	156	156	156	156	156
R-squared	0.268	0.608	0.420	0.454	0.433	0.545	0.545	0.143

*Note: The significance level is denoted by *, with *** being a significance level of 1%. Using the same regressions as in Table 5.2.*

Table 5. 9 *Sector FF3 - Subperiods*

Period:	GFC							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Index:	**REIT**	**Financial**	**Healthcare**	**Tech**	**Cons-Sta**	**Cons-Dis**	**Industry**	**Other**
S&P500	1.153***	0.914***	0.860***	1.273***	0.808***	1.122***	1.140***	1.075***
	(0.130)	(0.0829)	(0.0754)	(0.0899)	(0.0715)	(0.144)	(0.0710)	(0.141)
SMB	0.808***	-0.111	0.545**	1.009***	0.385**	1.144***	0.719***	1.380*
	(0.282)	(0.133)	(0.208)	(0.155)	(0.159)	(0.365)	(0.198)	(0.727)
HML	0.986***	1.210***	-0.0433	-0.318***	0.0824	0.531**	0.154*	0.428
	(0.351)	(0.0806)	(0.185)	(0.111)	(0.0870)	(0.208)	(0.0851)	(0.272)
a	0.00820	0.00792**	0.00910**	0.00934**	0.0142***	0.0110	0.0116***	0.0173
	(0.00755)	(0.00357)	(0.00440)	(0.00419)	(0.00372)	(0.00653)	(0.00350)	(0.0122)
n	36	36	36	36	36	36	36	36
R-squared	0.828	0.939	0.799	0.915	0.867	0.840	0.937	0.591
Period:	**Covid-19**							
S&P500	0.692**	0.602***	0.419*	0.792***	0.564***	1.116***	0.787***	0.160
	(0.250)	(0.194)	(0.229)	(0.193)	(0.169)	(0.231)	(0.182)	(0.483)
SMB	0.108	0.584	0.321*	0.446	0.295	0.501*	0.310	0.874
	(0.424)	(0.356)	(0.183)	(0.273)	(0.180)	(0.262)	(0.312)	(0.588)
HML	0.273	0.643***	-0.186	-0.142	0.0666	0.200	0.164	-0.139
	(0.296)	(0.152)	(0.154)	(0.152)	(0.137)	(0.231)	(0.191)	(0.485)
a	0.00731	0.00866	0.00873	0.0118	0.00905	0.00741	0.00889	0.0266
	(0.0145)	(0.0111)	(0.00993)	(0.0101)	(0.00858)	(0.0124)	(0.0108)	(0.0239)
n	25	25	25	25	25	25	25	25
R-squared	0.383	0.637	0.297	0.566	0.518	0.665	0.546	0.086

*Note: The significance level is denoted by *, with *** being a significance level of 1%. Using the same regressions as in Table 5.2.*

Estimates from the sector-specific regressions corroborate the findings from the REIT-only regressions. Market risk coefficients are reduced as the other risk factors explain a greater portion of the risk. Two main findings from the three tables are worth mentioning; firstly, in the 00-06 period, REIT stocks exhibited significantly lower risk than the 00-22 and 10-22 periods, as we observed before. This difference is not adjusted by an upward change in the standard error in the 00-06 regression. A similar pattern is observed for the financial portfolio though not for any other portfolios, suggesting that it only is an issue with some of the data. These findings suggest the possibility of fundamental issues in the data or the assumptions underlying the regression. To correct for it, a bootstrap regression[20] is utilised and presented

[20] A bootstrap or bootstrapped regression refers to checking the bias of an estimator by repeatedly drawing similar-sized samples through resampling the original. Then applying the model to the resample using different levels of repetitions Porta, M. (2016). Bootstrap. In: Oxford University Press.

in Appendix B to check the standard errors, but it refutes the idea that the estimated robust standard errors differ strongly from bootstrapped standard errors. Secondly, the elevated risk associated with the tech sector could be attributed to a strong correlation with the S&P500, though this is more evident in later periods. Although it could also be the effect of growth stocks outperforming value stocks represented by a negative HML factor, where the CAPM model then catches much of the risk otherwise captured by the other risk factors in the market risk beta and the residuals.

Table 5.10 below reports the expected returns given the estimated sector-specific CAPM and FF3 betas. Expected returns calculated using the CAPM are higher in the post-GFC period than they are pre-GFC. In contrast, the opposite is the case for expected returns calculated using the FF3 model, which likely is linked to the FF3 factors not being statistically significant post-GFC.

Based solely on the estimated CAPM betas from Table 5.7, it would be assumed that the highest expected return would be in the tech sector. Followed by the consumer discretionary, industrials, financials, and “other” sectors, as they all had similarly high and significant beta estimates. At the same time, the lowest expected returns should be found among the REIT, consumer staples and healthcare sectors. A similar pattern, with a few deviations, is expected to be present in the 00-06 and 10-22 periods. Based on the monthly expected returns of Table 5.10, the risk was compensated in the order expected, with the lowest market risk having the lowest expected returns in REIT, healthcare, and consumer staples sectors. Though only in the full sample period and the 10-22 period, with REIT stocks having the highest expected returns and tech stocks having the lowest and negative expected returns in 00-06. Meaning that the assumed linear relationship did not hold for the 00-06 period.

The mentioned negative returns in tech during the 00-06 period can be explained by the market premium being negative. Estimated as the difference between the expected returns for the S&P500 and the expected return on the risk-free rate approximated by 1-month T-bills. Therefore, the high market beta, in conjunction with the negative market premium, leads to negative expected returns. Moreover, during this period, the expected return on the HML factor was relatively high, while the estimated HML beta was significant and negative, resulting in overall negative expected returns.

The GFC period exhibits a pattern where sectors with high levels of risk experience more considerable losses when looking at the monthly expected returns. On top of this, the expected returns on HML stocks during the crisis were negative, as previously mentioned, indicating that value stocks performed worse than growth stocks. Given that the tech and healthcare sectors had negative HML betas, the losses in these sectors are expected to be smaller, as the model estimates a positive relationship, see Equation 4.5. On the other hand, the consumer staples sector in column 5 also had relatively lower risk estimates, leading to lower expected losses in general. The REIT and financial sectors in columns 1 and 2 had the highest expected monthly losses, closely followed by consumer discretionary, with industrials (7) and "other" (8) having middle-of-the-tree expected returns (losses).

Table 5. 10 *Sector-specific Expected Returns*

Period:				**2000-2022**				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Index:	**REIT**	**Financial**	**Healthcare**	**Tech**	**Cons-Sta**	**Cons-Dis**	**Industry**	**Other**
CAPM	0,36 %	0,43 %	0,36 %	0,55 %	0,32 %	0,48 %	0,44 %	0,41 %
FF3	0,53 %	0,65 %	0,42 %	0,57 %	0,42 %	0,66 %	0,60 %	0,49 %
Period:				**2000-2006**				
CAPM	0,20 %	0,10 %	0,11 %	-0,18 %	0,16 %	0,02 %	0,08 %	0,02 %
FF3	0,93 %	0,80 %	0,53 %	-0,16 %	0,82 %	1,10 %	1,12 %	0,52 %
Period:				**2010-2022**				
CAPM	0,55 %	0,79 %	0,58 %	0,81 %	0,55 %	0,86 %	0,81 %	0,51 %
FF3	0,50 %	0,63 %	0,53 %	0,76 %	0,49 %	0,75 %	0,70 %	0,47 %
Period:				**GFC**				
FF3	-0,96 %	-1,05 %	-0,30 %	-0,37 %	-0,35 %	-0,94 %	-0,56 %	-0,54 %
Period:				**Covid-19**				
FF3	0,87 %	0,82 %	0,58 %	1,05 %	0,74 %	1,44 %	1,02 %	0,34 %

Note: Table 5.10 presents the sector-specific expected returns, and only FF3 expected returns for the two special periods. The formulas used to calculate expected returns are the same as in Table 5.4.

5.3.1 The Optimal Portfolio

Before estimating the optimal portfolio for comparison with the CAPM results, the periods used should be as close to perfect as possible. To achieve this, I check the smaller periods for non-normality to see if the skewness and kurtosis estimated in Table 3.2 lead to significant deviation from normality in the data. To examine the normality of the data, I employ the Shapiro-Wilk test, which is considered the optimal choice for assessing the normality of a data sample (Ghasemi & Zahediasl, 2012). In doing this, I also assume that the central limit theorem applies to the two bigger periods: the full sample 00-22 and the 10-22 samples period with respective sizes of 276 and 156 observations. The test is presented and explained in Appendix B. Based on the results from the test; it is the case that during the 00-06 period, both consumer sectors, the industrial and "other" sectors followed a normal distribution with the rest of the sectors following a non-normal distribution. Furthermore, the GFC sample test indicates that the REIT, healthcare, tech, and consumer staples sectors are normally distributed. Lastly, all sectors but "other" were estimated to be normally distributed during Covid-19. Since the 00-06 period was influenced by most of the data being non-normal, it is extended to cover the GFC period, becoming the combined 00-09 period, which, when checked with the Shapiro-Wilk test, only had one non-normal sector, being industrials.

The sector data is used to find the return on the overall portfolio consisting of all the sectors (referred to as the optimal portfolio from here on out), given an arbitrary starting point for the weight of each sector. The starting point for the weights is the equal weighting of 12.5% in each sector. Following this, the covariance, returns, volatility and Sharpe Ratio[21] are found for the optimal portfolio in each of the three periods being 00-22, 00-09 and 10-22. The Sharpe ratio is going to be defined by the weightings in the mean-variance efficient portfolios.

The optimal portfolio composition is found by simulating the baseline weights to maximise the Sharpe ratio. This is done by finding the weights that minimise the volatility, where the volatility is a product of a covariance matrix of the sectors, and maximising the return of the portfolio, which is a product of the weighted average returns for each sector. The simulation is

[21] The Sharpe Ratio is a measure of returns per unit risk and is calculated as the excess return of an asset divided by its volatility, see Fernando, J. (2023). *Sharpe Ratio Formula and Definition With Examples*. Investopedia. https://www.investopedia.com/terms/s/sharperatio.asp. Therefore, it will be used to calculate the mean-variance efficient portfolios.

constrained to using a minimum weight of 5% for each sector, and short selling is, by extension, not allowed. This means that both systematic and idiosyncratic risk is included in the volatility, but as argued from Figure 5.1 and Tables 5.7 to 5.9, there exists a pattern of high-volatility stocks also having relatively higher systematic risk. In Table 5.11 below, the optimal portfolio is reported together with the baseline portfolio created using equal weights for each sector. Where $E(RP)$ is the expected return on the portfolio, $Vol(P)$ is the volatility of the portfolio and "$Sharpe$" is the Sharpe ratio of the portfolio, with all sizes reported in percentages.

Equal-weighted portfolios of the sectors produce higher portfolio returns in the 00-22 sample and 10-22 subperiod, though being strongly outperformed in all periods when considering the Sharpe Ratio. The sectors consistently included with higher-than-5% in the optimal portfolio are consumer staples, consumer discretionary, healthcare and "other". With the rest being locked at 5% in every period. Finding high allocations into consumer staples and healthcare is unsurprising as both stocks had low risk and consistent expected returns in the CAPM and FF3 models. On the other hand, REIT stocks have low weightings in both the full sample and the 00-09 period. This can largely be attributed to the influence of the GFC on the volatility in the sector. Though REIT stocks arguably could be included in the 10-22 period, they did not give higher expected returns given the level of systematic risk, as observed in Tables 5.7, 5.8 and 5.10, than the other two low-risk sectors.

The choice of which riskier asset to be included in the optimal portfolio is of interest, with consumer discretionary having large weights in all periods. The inclusion of the "other" sector in the 00-22 and 10-22 periods implies that one or more of the sectors included in it provides good risk-return relationships in an optimal portfolio. Based on Figure 5.1, there is no obvious candidate for inclusion among the financials, tech, consumer discretionary, industrials and "other" sectors, with estimated market risk also being similar among the optimal candidates. The reason behind the weighting of consumer discretionary can be attributed to the main candidate when looking at expected returns, being tech, being excluded given the sector's high relative systematic risk. The second in line considering expected return and relative systematic risk from Tables 5.7, 5.8 and 5.10 is consumer discretionary, being the reason behind its inclusion as the riskier asset in the optimal portfolio. A similar story can be told for the “other” sector while being more ambiguous given the four sectors included in it.

Table 5. 11 *Optimal Portfolios*

00-22				Weights							
	E(RP)	**Vol(P)**	**Sharpe**	**Financials**	**Healthcare**	**Tech**	**ConsDisc**	**ConsStap**	**REIT**	**Industrials**	**Other**
EW	0,79 %	3,10 %	25,56 %	12,5 %	12,5 %	12,5 %	12,5 %	12,5 %	12,5 %	12,5 %	12,5 %
Optimal	0,74 %	1,82 %	40,76 %	5 %	19 %	5 %	33 %	21 %	5 %	5 %	7 %
00-09											
	E(RP)	**Vol(P)**	**Sharpe**								
EW	0,72 %	3,35 %	21,56 %	12,5 %	12,5 %	12,5 %	12,5 %	12,5 %	12,5 %	12,5 %	12,5 %
Optimal	0,85 %	1,94 %	43,81 %	5 %	16 %	5 %	37 %	23 %	5 %	5 %	5 %
10-22											
	E(RP)	**Vol(P)**	**Sharpe**								
EW	0,85 %	2,92 %	29,11 %	12,5 %	12,5 %	12,5 %	12,5 %	12,5 %	12,5 %	12,5 %	12,5 %
Optimal	0,68 %	1,64 %	41,19 %	5 %	28 %	5 %	20 %	20 %	5 %	5 %	12 %

Conducting a period-by-period analysis might have given different weights in addition to conforming to the CAPM assumptions of single-period investor decisions, the results would not be realistic if real estate is assumed to be illiquid.

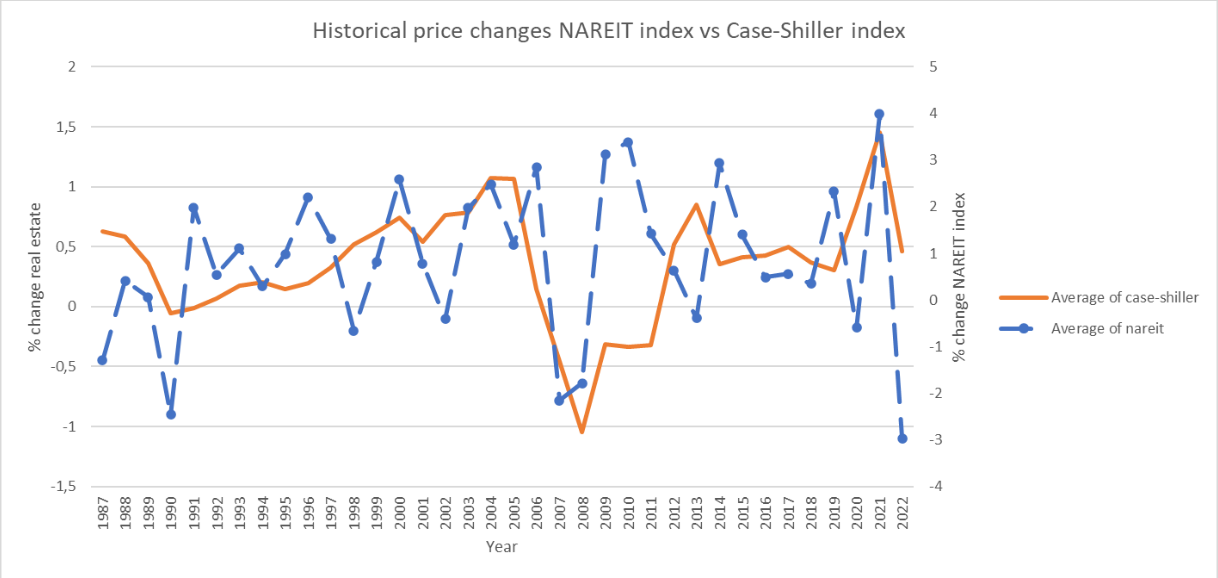
5.3.2 Issues Surrounding Rare Events

Residential real estate seems relatively stable over time when looking at the estimates from both CAPM and FF3 models, while the graphical representation tells a story of a single rare event cutting returns significantly. In Figure 5.2 below, the Case-Shiller repeat sales index (S&P Dow Jones Indices LLC, 2023b) has been graphed together with the NAREIT index[22] (NAREIT, 2023), both on percentage change form. Both return series follow a similar pattern as far as rare events go, while the REIT returns are more volatile over time. The difference in volatility can be largely attributed to the previously discussed difference in income between REITs and house-price indices, with the Case-Shiller index only being based on sales and not rental income. Not to forget the general difference in volatility between the stock market and real estate. The previously assumed size of the 1990s recession disappears in comparison to the GFC, implying that it might not help to unfold the effect of rare events on residential REITs.

[22] Note that this index is based on all equity REIT returns until 1994, from there it is only residential REIT index returns.

The main challenge lies in determining the effect of the rare event and finding out if it significantly impacts both beta coefficients and standard errors. If such rare events are more severe, and less rare for one asset group, that should impact its portfolio weight. Wachter (2020) outlines how difficult it is to learn about and consider rare events given their non-constant probability of happening while highlighting that they should be considered a significant risk factor in asset pricing. One would wish to quantify the impact of the event over time together with the probability of it happening, but the challenge is that it is difficult given the varying size and intervals between each event. In addition to not being a well-covered subject in the literature, which limits the understanding and measures to correct data influenced by rare events.

Figure 5. 2 *Historical NAREIT Index vs Case-Shiller Index*



To examine the possibility that a more extended data series might correct some of the bias from the assumptions of statistical software, I scrape all available equity REIT data, residential REIT data and S&P500 data back to 1985[23]. Two portfolios are created by averaging the existing REITs each month, with the results from the CAPM and FF3 regressions reported in Table 5.12 below. Results from the regressions using the portfolios

[23] It is impossible to access data further back than 1985 on Yahoo Finance. Despite the data being reported existing.

bring up a previously highlighted point: residential REIT data differs from the rest of the REIT sectors in risk profile. Furthermore, coefficients and standard errors are very similar to the 00-22 period, being slightly lower, which likely is caused by a large increase in observations. Implicating that a period that also consist of a previous recession does not change the coefficients and standard errors for residential REITs. Although the data could go further back in both Table 5.12 and Figure 5.2 to capture more of the risk leading up to the '90s recession, that probably would not be more meaningful. Firstly, because by that logic, the observation period could be extended indefinitely, and secondly, because of the assumptions such an extension of the observation period brings. A low number of equity REITs existed in data during 1985 and into the 1990s, with the residential REIT data only consisting of two stocks in 1985, which only increased to a number higher than four in the mid-90s. The issue this raises is the one that was assumed non-existent in the shorter data series. The question of survivorship bias becomes prevalent and a potential issue during the estimation of betas and standard errors. Return series calculated early on will also be highly affected by the different firms' capital structure slowly being added to the data over time, potentially skewing the data in unknown ways.

Lastly, the high coefficients on all equity REIT data implicate big differences between real estate industries. It supports the claim made in this thesis that they cannot be analysed together as they do not represent the same thing.

Table 5. 12 *Equity REIT Regressions vs Residential REIT Regressions*

Period:	**1985-2022**				**2000-2022**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Portfolio:	**Equity**	**Equity**	**Residential**	**Residential**	**Equity**	**Equity**	**Residential**	**Residential**
S&P500	1.156**	1.104**	0.599***	0.603***	1.561*	1.691**	0.734***	0.694***
	(0.513)	(0.533)	(0.0728)	(0.0598)	(0.803)	(0.750)	(0.0883)	(0.0715)
SMB		-0.286		0.479***		-0.966		0.312***
		(1.001)		(0.0805)		(1.487)		(0.0887)
HML		-0.896		0.462***		-1.580		0.385***
		(1.038)		(0.0858)		(1.307)		(0.0990)
a	0.0827***	0.0848***	0.00611***	0.00507**	0.134***	0.139***	0.00936***	0.00791***
	(0.0298)	(0.0318)	(0.00223)	(0.00204)	(0.0484)	(0.0531)	(0.00266)	(0.00253)
n	455	455	455	455	276	276	276	276
R-squared	0.007	0.008	0.254	0.373	0.008	0.013	0.370	0.446

6 Limitations and Possible Extensions

The question of robust standard errors somewhat correcting the issue of biased estimation in the analysis is difficult to answer. Imbens and Kolesar (2016) argue that robust standard errors are biased downwards in smaller samples, as they rely on larger samples for validity. The downward bias in the robust standard errors included in statistical software can be the cause for the discrepancy observed for the 00-06 period in Chapter 5. The fact that the robust standard errors were similar to the standard errors from the bootstrap regression means that they are more credible than the non-robust standard errors. However, a question can be raised regarding the inference that can be drawn from a simple thousand-repetition bootstrap. The bootstrapped regressions should have consisted of a higher number of repetitions, though while that could have improved the standard errors, it would have been computationally time-consuming.

Limited data availability provided a challenge; for one thing, leverage significantly affected REIT risk and return, but it cannot be compared to the other stock sectors. This limits the inference that can be drawn from it, in addition to the issue of using yearly leverage data on monthly stock returns. This also highlights the second issue regarding extending the data series to examine the effect of rare events. Extending the data raises a question of survivorship bias and data mining, as using only residential real estate in the general analysis also could be considered datamining. Though I argued for excluding the other REIT industries, I did not provide qualitative or quantitative reasoning other than the direct comparison with all equity REITs in Chapter 5.3.2. The time and space in the thesis needed to conduct a proper analysis of the differences between REIT industries would likely be a master thesis in itself. Given more time, the other GICS sectors could also have been scraped and analysed based on the 1990s regression to be compared with real estate. I also acknowledge that I did not examine the sub-periods surrounding the 1990s recession, where the original discrepancy was found in the 00-06 subperiod. This must then be the subject of further research as the issue might lie in investor expectations leading up to and following rare events, with the risk being lower before and higher after the event.

The strength of the REIT proxy is discussed and highlighted in the thesis, though it remains ambiguous and primarily based on qualitative assumptions. The challenges surrounding the proof of the optimal proxy lie in limited data availability. Data that covers rental and related costs could be used to directly analyse how income and costs connected to owning the underlying real estate can be connected to REIT returns. However, without access to comparable income data, the assumptions made in the thesis are necessary.

Lastly, macro data was included in the dataset and could be an interesting avenue for future research as the sensitivity of the different sectors could be important in determining the optimal portfolio. Similarly, neglected assets like corporate bonds and possibly cryptocurrency could be included and analysed with stocks and real estate. The optimal portfolio in Chapter 5 could also have been estimated using sensitivity analysis with simulations of different volatility and return values for each sector. However, the choice fell on basing the portfolio on the similarities between volatility and betas in Figure 5.1 and Tables 5.7 and 5.8.

7 Summary and Conclusion

This thesis aimed to find the position of residential real estate in an optimal portfolio consisting of all the sectors defined by the GICS. First, the thesis linked REIT data to residential real estate, creating a dataset containing over 500 stocks divided over the eight defined sectors from 2000 to 2022. The thesis then introduced the asset pricing models and theories used to examine the risk and return of real estate and to help assess residential real estate's position in an optimal portfolio. Theoretical fundamentals like the propositions of capital structure by Modigliani and Miller (1958) was brought into the discussion, with the assumptions of both the MM theory and CAPM assumptions falling short in the presence of rare events such as the GFC.

The analysis compared real estate with the other stock sectors, with REIT stocks proving to be among the less risky sectors when considering systematic risk. The thesis found a relationship where sectors exhibiting low volatility similarly exhibited low systematic risk and vice versa. Consumer staples, healthcare and REIT sectors being among the low-risk stocks and tech, consumer discretionary and financials being among the high-risk stocks. Based on this finding, optimal portfolios were simulated based on mean-variance efficiency using Sharpe ratios to find the optimal allocation of funds into each sector; the results indicated what could be expected based on the CAPM and FF3 results. Consumer staples and healthcare were the two low-risk sectors consistently chosen in the portfolio over the REIT stocks in the 00-22 period and the two subperiods of 00-06 and 10-22. REIT stocks had a constant weight of 5% which can be attributed to a worse risk-return relationship than healthcare and consumer staples based on the asset pricing models, with its volatility also being highly influenced by the rare event of the GFC.

Among the riskier sectors, overall consumer discretionary had high weightings in all periods, while the "other" sector had higher-than-5% weightings in two periods. Consumer discretionary was included in the portfolio over industrials, financials and tech, as it had the lowest risk given expected returns based on the asset pricing models. Tech was close second, though negatively influenced by having the highest systematic risk of any sector across all periods. The reason being that the linear relationship assumed by the CAPM model failed, and tech had worse expected returns than consumer discretionary. The other sectors were middle of the pack as far as relative risk and return goes, justifying the consistent 5% weighting. Lastly the thesis extended the period of the REIT sector to account for the GFC, though the results did not change significantly.

Real estate could fit into the optimal portfolio over healthcare and consumer staples, with it having a similar low risk and return relationship to those two sectors. The implication being that real estate is defined by low risk and expected return over the full period, but in the choice of the optimal portfolio diversification when utilising all sectors, will get a low weight. The reason being that among the low-risk stocks it is not the optimal choice while it does not compete with the high-risk high return stocks either. This result can be tied together with the GFC to a certain extent. Although this thesis did not find any conclusive evidence of the significance of the crisis on real estate risk and returns in periods that did not include the 07-08 GFC period.

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Appendix

Appendix A – Supplement to Chapter 4

The Augmented Dickey-Fuller test is used to test for stationarity or if data possesses random walk qualities. It is used with a regression on the form:

$$x_t = \mu + \gamma_t + \sum_{j=1}^{p} \alpha_j y_{t-1} + u_{it}$$

Where t is the linear trend in the data, we are testing for alpha being equal to 0. If we change the formula to one of change from one period to the next, it becomes:

$$\Delta x_t = \mu + \gamma t + \alpha x_{t-1} + \sum_{j=1}^{k-1} \beta_j \Delta x_{t-j} + u_t$$

The null and alternative hypotheses being defined as follows:

$$H_0: \alpha = 0 \ vs \ H_A: \alpha < 0$$

And the goal is to check for alpha is equal to zero; if not, then the process is stationary. As the data covers a wide timespan, the augmented Dickey-Fuller test checks more periods covered by the right side of the summation.

The augmented equation is found in Cheung and Lai (1995) and (Holmes et al., 2020), where the equations are based on the original by Dickey and Fuller (1979). The test produces an ADF statistic which is rejected based on a p-value. The null hypothesis is that the time series has a unit root, that being that it is non-stationary. The alternative hypothesis is that the time series has no unit root; it is stationary. The results are presented in Table A.1. Where the only non-stationary series is the risk-free rate and the FHFA index. Given the risk-free rate never being directly included in regressions, it is kept as is. The FHFA index was not used as the MSA index was superior in Chapter 5 and is kept for that reason. The series could be differentiated if needed.

Table A.1 ***Stationarity Test***

	ADF-stat	P>0		ADF-stat	P>0
REIT	-6,70***	0.000	**Cons-staples**	-7.90***	0.000
Financials	-12,56***	0.000	**Cons-disc**	-6.16***	0.000
Healthcare	-15.64***	0.000	**Industrials**	-7.92***	0.000
Tech	-16,74***	0.000	**Other**	-15.62***	0.000
S&P500	-16.26***	0.000	**SMB**	-14.28***	0.000
HML	-14.35***	0.000	**rf**	-1.82	0.367
FHFA-Index	-1.43	0.567	**MSA-Index**	-3.47**	0.008

Note: Table A.1 presents the results of the Augmented Dickey-Fuller (ADF) test for stationarity.

Table A.2 presents the Durbin-Watson statistics and to what degree autocorrelation exists. The statistic is estimated based on the CAPM time-series regression. With the test statistic being estimated in statistical software post-regression.

The 4-DL represents the cut-off where values above are defined as showing negative autocorrelation, meaning that the DW-stats over 2, where a stat of 2 means zero autocorrelation, is in either a grey area or defined as being a series of negative autocorrelation. All indices had DW-stats over 2. While most were in a grey area defined by the 4-DL cut-off, most showed no autocorrelation over the whole sample.

Table A.2 ***Durbin-Watson Test***

Period:	**2000-2022**	**DW-stat**		**4-DL**
REIT		2,18	<	2,24
Financials		2,33	>	2,24
Healthcare		2,06	<	2,24
Tech		2,52	>	2,24
Cons Staples		2,19	<	2,24
Cons Disc		2,21	<	2,24
Industry		2,52	>	2,24
Other		2,27	<	2,24

Note: Table A.2 presents the results from the Durbin-Watson test.

Appendix B – Supplement to regressions

Summary statistics for all eleven REITs included in the dataset are reported in Table B.1. In the table, the REITs are sorted in descending order based on their market cap from the highest market cap at "Equity Residential" to lowest at "BRT Apartments", the mean and standard errors are estimated based on the excess return of each of the REITs, meaning the arithmetic return less the risk-free rate (1-month T-bills). Summary statistics are not supplied for the other sectors, given the large number of stocks compared to the residential REIT index.

Table B.1 ***REIT Stocks Descriptive Statistics***

Period:	2000-2022		2000-2006		2010-2022		GFC		Covid-19	
	Mean	ST.DEV	Mean	ST.DEV	Mean	ST.DEV	Mean	ST.DEV	Mean	ST.DEV
exeqr	0,91 %	6,64 %	1,42 %	5,43 %	0,91 %	5,83 %	-0,24 %	11,15 %	1,00 %	8,37 %
exavb	1,04 %	6,63 %	1,89 %	5,07 %	0,91 %	6,08 %	-0,42 %	10,81 %	1,28 %	8,57 %
exmaa	1,23 %	6,13 %	1,63 %	4,76 %	1,21 %	5,41 %	0,38 %	10,51 %	2,30 %	7,24 %
exsui	1,26 %	7,60 %	0,43 %	4,83 %	1,87 %	6,44 %	0,55 %	14,56 %	1,40 %	7,92 %
exess	1,09 %	6,41 %	1,90 %	5,26 %	1,05 %	6,16 %	-0,60 %	9,21 %	0,99 %	8,12 %
exudr	1,09 %	6,89 %	1,89 %	5,50 %	1,01 %	5,65 %	-0,46 %	12,52 %	1,33 %	7,74 %
excpt	1,08 %	7,07 %	1,55 %	4,74 %	1,15 %	5,99 %	-0,31 %	13,34 %	2,25 %	7,95 %
exvre	0,46 %	8,20 %	1,31 %	5,63 %	0,05 %	7,70 %	0,25 %	13,72 %	-0,77 %	9,68 %
exaiv	1,11 %	10,15 %	0,93 %	6,16 %	1,52 %	9,38 %	-0,26 %	18,08 %	2,63 %	18,20 %
exumh	0,94 %	7,51 %	1,21 %	5,75 %	1,18 %	7,89 %	-0,70 %	9,24 %	2,51 %	10,48 %
exbrt	1,20 %	10,12 %	2,02 %	6,70 %	1,41 %	8,87 %	-1,60 %	18,43 %	2,48 %	13,12 %

The volatility in all periods is, on average higher for the REITs with lower market capitalisation, and they also see the highest mean return for the periods where they reach the highest levels of volatility. But, again, this is apart from the financial crisis.

Table B.2 reports the dataset's estimated beta values for each REIT. The 00-06 period is one of low systematic risk, as could be expected, while the GFC and the Covid-19 periods see higher beta values, the same goes for the other two bigger sample periods. But the bigger samples are top heavy given the trend in 00-06, so most of the observed REIT risk comes after 2006.

Table B.2 ***Individual REIT Stocks CAPM Betas***

CAPM					
Period	**2000-2022**	**2000-2006**	**2010-2022**	**GFC**	**Covid-19**
exeqr	0.703***	0.399**	0.573***	1.421***	0.858***
exavb	0.766***	0.367**	0.688***	1.485***	1.049***
exmaa	0.607***	0.338***	0.498***	1.254***	0.688**
exsui	0.710***	0.0601	0.559***	1.837***	0.472
exess	0.607***	0.240*	0.609***	1.055***	0.934***
exudr	0.629***	0.112	0.603***	1.346***	0.810**
excpt	0.798***	0.268**	0.658***	1.836***	0.789**
exvre	0.798***	0.213	0.722***	1.814***	0.861**
exaiv	0.763***	0.208	0.372**	2.338***	0.461
exumh	0.548***	-0.174	0.727***	0.984***	0.976**
exbrt	0.663***	0.253	0.510**	1.548***	0.745

FF3					
Period:	**2000-2022**	**2000-2006**	**2010-2022**	**GFC**	**Covid-19**
exeqr	0.663***	0.573***	0.525***	0.959***	0.752**
exavb	0.722***	0.524***	0.651***	1.164***	0.958***
exmaa	0.567***	0.447***	0.489***	1.004***	0.673**
exsui	0.672***	0.188	0.602***	1.321***	0.569*
exess	0.561***	0.357***	0.565***	0.748***	0.832***
exudr	0.559***	0.244	0.550***	0.823***	0.718**
excpt	0.741***	0.391***	0.627***	1.353***	0.746**
exvre	0.724***	0.364**	0.604***	1.330***	0.715*
exaiv	0.685***	0.395***	0.255	1.840***	0.217
exumh	0.480***	-0.0287	0.603***	1.049***	0.887**
exbrt	0.569***	0.328*	0.362*	1.092**	0.543

Table B.3 lastly presents the correlations among the REIT stocks. Again, there is a stronger correlation among stocks with large market caps than between large and low-low cap stocks. This implies that increased returns in large-cap REIT stocks could have more spillover among other large-cap REIT stocks than small-cap stocks.

Table B.3 ***Individual REIT Stocks Correlations***

	eqr	avb	maa	sui	ess	udr	cpt	vre	aiv	umh	brt
eqr	1	0,838997	0,686437	0,593591	0,789925	0,740166	0,758115	0,571533	0,5929	0,363577	0,314168
avb	0,838997	1	0,714448	0,620208	0,84108	0,775477	0,818247	0,60698	0,61531	0,412505	0,316081
maa	0,686437	0,714448	1	0,582595	0,671123	0,686554	0,734202	0,580429	0,526389	0,293207	0,299054
sui	0,593591	0,620208	0,582595	1	0,545135	0,585126	0,692621	0,520794	0,535517	0,360948	0,379995
ess	0,789925	0,84108	0,671123	0,545135	1	0,745252	0,757799	0,513808	0,548927	0,374087	0,268708
udr	0,740166	0,775477	0,686554	0,585126	0,745252	1	0,739145	0,558026	0,578477	0,340206	0,384393
cpt	0,758115	0,818247	0,734202	0,692621	0,757799	0,739145	1	0,59037	0,613019	0,417703	0,413348
vre	0,571533	0,60698	0,580429	0,520794	0,513808	0,558026	0,59037	1	0,465584	0,37048	0,402537
aiv	0,5929	0,61531	0,526389	0,535517	0,548927	0,578477	0,613019	0,465584	1	0,412061	0,348052
umh	0,363577	0,412505	0,293207	0,360948	0,374087	0,340206	0,417703	0,37048	0,412061	1	0,309616
brt	0,314168	0,316081	0,299054	0,379995	0,268708	0,384393	0,413348	0,402537	0,348052	0,309616	1

The robustness of the standard errors given the statistically significant result in Tables 5.7, 5.8 and 5.9 of Chapter 5 is checked using a bootstrap with a thousand repetitions. These are all presented in Table B.4 below. While standard errors changed when using the bootstrap, the ones estimated using the original robust regression were not different to the extent that it would change the significance. In contrast, using non-robust regressions gave lower standard errors. Therefore, robust standard errors corrected some biases that would otherwise be present.

Table B.4 ***Bootstrapped Standard Errors***

Period:				**2000-2022**				
CAPM	**REIT**	**Financial**	**Healthcare**	**Tech**	**Cons-Sta**	**Cons-Dis**	**Industry**	**Other**
se(bM)	.0986	.0768	.0671	.0942	.0525	.0923	.0734	.0973
Period:				**2000-2006**				
se(bM)	.0930	0.0755	.1336	.1770	.0730	.1214	.0974	.0970
Period:				**2010-2022**				
se(bM)	.12030	.12060	.09150	.1219	.07894	.14087	.12040	.15597

Period:				**2000-2022**				
FF3	**REIT**	**Financial**	**Healthcare**	**Tech**	**Cons-Sta**	**Cons-Dis**	**Industry**	**Other**
se(bM)	.08345	.05520	.06557	.08785	.04570	.077845	.06152	.09415
se(SMB)	.09389	.06647	.10734	.13639	.05799	.12394	.08526	.12470
se(HML)	.10488	.07282	.07258	.09830	.05744	.09424	.06939	.15000
Period:				**2000-2006**				
se(bM)	.08514	.05922	.11739	.14108	.04963	.09838	.06647	.09604
se(SMB)	.10797	.07285	.14507	.16988	.06916	.14515	.09443	.08754
se(HML)	.14027	.11569	.12765	.15853	.06449	.14506	.09142	.11406
Period:				**2010-2022**				
se(bM)	.11008	.0949	.0962	.13029	.0853	.1256	.110099	.15183
se(SMB)	.16932	.13309	.0996	.14349	.0982	.1350	.1394	.21406
se(HML)	.1583	.11754	.1082	.1441	.08463	.15307	.1214	.22480

Note: Table B.4 Provides the bootstrapped standard errors from the regressions used in Tables 10, 11 and 12, the standard error for each beta is reported in the order they are presented in those tables.

In Tables B.1, B.2 and B.3, the results from the Shapiro-Wilk test are reported. If the p-value of the test is greater than 0.05 (α level), we cannot reject the null hypothesis that the data is normally distributed. On the other hand, if the p-value is smaller than or equal to 0.05, we can reject the null hypothesis and say that the variable is not normally distributed. The “r” preceding the variable in the tables refers to the residuals from a regression using the variable.

The new period of 00-09 is also presented in Table B.8, with only industrials being non-normal, though the central limit theorem is assumed to hold for the period, as was also the case for the other periods with high observations.

Table B.5 ***Shapiro Wilk test 00-06***

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
rreit	84	0.96663	2.385	1.909	0.02811
rfin	84	0.95143	3.471	2.734	0.00313
rhealth	84	0.82579	12.447	5.540	0.00000
rtech	84	0.89672	7.380	4.391	0.00001
rconssta	84	0.98859	0.815	-0.449	0.67328
rcondis	84	0.98927	0.767	-0.583	0.72012
rind	84	0.98277	1.231	0.457	0.32397
rother	84	0.97280	1.943	1.459	0.07222

Table B.5 presents the Shapiro-Wilk test on the 00-06 period of the data.

Table B.6 ***Shapiro Wilk test GFC***

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
rreit	36	0.98753	0.455	-1.648	0.95028
rfin	36	0.93883	2.230	1.677	0.04673
rhealth	36	0.96920	1.123	0.243	0.40412
rtech	36	0.97226	1.011	0.024	0.49052
rconssta	36	0.97725	0.829	-0.391	0.65213
rcondis	36	0.89154	3.955	2.875	0.00202
rind	36	0.89656	3.772	2.776	0.00275
rother	36	0.68013	11.664	5.137	0.00000

Table B.6 presents the Shapiro-Wilk test on the GFC period of the data.

Table B.7 ***Shapiro Wilk test Covid-19***

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
rreit	25	0.97774	0.618	-0.982	0.83704
rfin	25	0.95400	1.278	0.502	0.30790
rhealth	25	0.97377	0.729	-0.647	0.74115
rtech	25	0.95272	1.314	0.558	0.28851
rconssta	25	0.98146	0.515	-1.356	0.91239
rcondis	25	0.92601	2.056	1.473	0.07033
rind	25	0.98661	0.372	-2.021	0.97835
rother	25	0.79286	5.756	3.578	0.00017

Table B.7 presents the Shapiro-Wilk test on the Covid-19 period of the data.

Table B.8 ***Shapiro Wilk test 00-09***

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
rreit	120	0.96941	2.943	2.419	0.00779
rfin	120	0.94832	4.973	3.594	0.00016
rhealth	120	0.84790	14.636	6.012	0.00000
rtech	120	0.89126	10.464	5.260	0.00000
exconssta	120	0.97014	2.874	2.365	0.00901
rcondis	120	0.96772	3.106	2.539	0.00555
rind	120	0.98706	1.245	0.491	0.31158
rother	120	0.70842	28.058	7.470	0.00000

Table B.8 presents the Shapiro-Wilk test on the 00-09 period of the data.