Building Momentum: An Exploration of Real Estate Operating Companies' Dynamics

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Abstract

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REIT returns are commonly subject to extensive research. However, the smaller subindustry of REOCs is neglected, despite being most prevalent form of real estate stocks in Europe. For REITs it has been established that momentum strategies are a viable investment opportunity.

This dissertation investigates the effectiveness of momentum strategies in European REOCs by conducting a comprehensive and systematic analysis of historical REOC returns. The primary objective is to determine whether momentum is prevalent between 1990 and 2023 as well as three sub-periods. Further, we want to see if those strategies can consistently generate excess returns throughout the total period and the subperiods. This research contributes to the existing body of literature on the topic, providing valuable insights for both practitioners and academics alike.

Our results indicate that the momentum effect is prevalent in the overall sample but more significant in the second subperiod where financial markets underperformed. Furthermore, we show that the REOC momentum strategy generates excess returns compared to the market suggesting that momentum investing can be a viable and profitable approach for market participants in the European real estate sector.

Keywords: *momentum strategy, real estate operating companies, investment strategy, financial performance, real estate, market efficiency*

Resumo

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Os retornos dos REITs são comumente objeto de extensa pesquisa. No entanto, a classe menor de REOCs quase nunca é analisada em detalhes, apesar de ser mais prevalente na Europa. Para os REITs, foi estabelecido que as estratégias de momentum são uma oportunidade de investimento viável.

Esta dissertação tem como objetivo investigar a eficácia das estratégias de momentum nos REOCs europeus, realizando uma análise abrangente e sistemática dos retornos históricos das ações. O objetivo principal é determinar se o momentum é prevalente entre 1990 e 2023, bem como em três subperíodos específicos. Além disso, queremos ver se essas estratégias podem gerar retornos consistentemente excessivos. Esta pesquisa contribui para o corpo existente de literatura sobre o tema, fornecendo informações valiosas para profissionais e acadêmicos.

Os nossos resultados indicam que o efeito momentum é prevalente na amostra geral, mas mais significativo em períodos em que os mercados financeiros apresentam um desempenho inferior. Além disso, demonstramos que os retornos long-short dos REOCs geram retornos excessivos em relação ao mercado, sugerindo que o investimento em momentum pode ser uma abordagem viável e lucrativa para os participantes do mercado no setor imobiliário europeu.

Palavras chave: *estratégia de momentum, empresas imobiliárias operacionais, estratégia de investimento, desempenho financeiro, imobiliário, eficiência de mercado*

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1. Introduction

The momentum effect, first documented by Jegadeesh and Titman (1993), is a well-established anomaly in financial markets, characterized by the tendency of past winning stocks to continue outperforming and past losing stocks to continue underperforming over short-term horizons. While the momentum effect has been extensively studied in the context of equity markets, no attention has been paid to its applicability to Real Estate Operating Companies (REOCs), a particular subtype of listed real estate companies. This thesis aims to analyse the momentum effect for REOCs between 1990 and 2023. We aim at understanding if the prevalence of momentum is significant over time and the look at the existence of excess returns in three different sub-periods namely 1991-2000, 2001-2010, and 2011-2020. We believe that this approach – based on research published by Chui, Titman and Wei – enables to gain a deeper understanding of REOC returns and helps us to understand if momentum is equally strong across cycles. Further, it will allow us to comment on the question if the return characteristics make it a viable investment strategy.

Despite a fair number of publications on Real Estate Investment Trusts (REITs), we believe that the behaviour of REOCs to REITs might be differ due to regulatory differences. The fact that contrary to REITs, REOCs are not required to distribute a majority of their earnings as dividends might contribute to the potential existence of a distinct momentum effect in this type of stocks. More control over the distribution of dividends might allow REOCs to retain more capital for growth and expansion despite of the overall structure being accompanied by tax disadvantages (Lorenz, 2009).

The existence of the momentum effect for REITs has been analysed by several different researchers over different periods of time with different angles, most notably by Chu, Titman and Wei (2003b). Yet there is no existing research on the existence of the momentum effect for REOCs so far. This is likely due to two factors. Firstly, REOCs are much less prevalent in the US due to comprehensive regulation of REITs. Secondly, the European market for listed real estate stocks developed significantly slower than the US limiting both the number of stocks analysed as well as the time horizon that can be researched.

Nonetheless, we believe that the study of the momentum effect in the context of REOCs is extremely interesting as REOCs are an essential component of the European real estate market, providing a more liquid and accessible investment vehicle compared to direct real estate investments (Bond and Hwang, 2005).

As outlined, the existing literature on the momentum effect in real estate markets is centred around REITs (Derwall et al., 2009; Chui, Titman, and Wei, 2003b) and others on direct real estate investments (Gyourko and Keim, 1992). These studies primarily focus on the US market, leaving a gap in the literature concerning the European market. Looking at the European market exclusively research is limited. Research on REOCs is also extremely scarce with one example being Lorenz (2009) research on market pricing and timing of SEOs of REITs compared to REOCs.

By analysing the momentum effect for REOCs, this thesis seeks to contribute to the existing literature and provide valuable insights into the performance of momentum-based investment strategies in the European real estate market. The analysis of the momentum effect in the REOCs market between 1990 and 2023 provides a valuable opportunity to investigate the impact of various economic events and market conditions on the momentum phenomenon. During this period, Europe experienced several notable events, such as the establishment of the European Monetary Union (EMU) in 1999, the global financial crisis of 2007-2008, and the subsequent European sovereign debt crisis (Lane, 2012). These events may have affected the risk-return characteristics of the European REOCs market and, in turn, influenced the momentum strategy performance.

Overall, in the last decades the European real estate market has changed significantly. The most common form of real estate ownership used to be direct investment due to the assets characteristics as non-standardized good, highly dependent on local legislation and lawmakers. However, throughout the last decades a myriad of indirect investment opportunities in real estate has transformed the asset class into an investable, tradable, financial product included in portfolios of many private and institutional investors and direct ownership of properties has been exchanged into fictitious capital in the form of shares of indirect investment vehicles (Aalbers, van Loon and Fernandes, 2017). The liberalization of financial markets and the integration of European economies have facilitated cross-border capital flows and enabled a more efficient allocation of resources and promoting the growth of the real estate sector (Eichholtz, 1997).

Consequently, the real estate market has become increasingly institutionalized, with a growing number of professional investors participating in the market. Real assets in Europe developed to be an attractive investment opportunity and an important element in mixed-asset portfolios Depending on the investment strategy indirect investment in real assets through REITs and REOCs has gained popularity (Newell and Worzalla, 1995).

Real assets are widely associated with stability and low volatility even in times of general market turmoil. This is the case even though the opinions on the question if real estate acts as a safe haven in market turmoil are far from unanimous in academia. There is an argument to be made that in times of a rapid decrease in market liquidity, illiquid assets are more vulnerable to negative returns (Brunnermeier and Pedersen, 2006).

Nonetheless, today, all major asset managers have allocated a significant share of the AUM to real assets invested directly through debt or equity and indirectly through holdings of listed real estate firms. Most of the funds invested in real estate indirectly is through REITs. REITs are different from common stock as they must adhere to different guidelines depending on the REIT regime such as income requirements or restrictions on the equity ratio. Most importantly REITs are characterized by an extremely high profit distribution mostly ranging from 80% to 95% of net profits (Lorenz, 2020). In the US REITs account for 99% of the market cap of listed firms in the real estate industry in the US. In Europe REITs only make up 43% of the market cap of listed real estate firms (EPRA, 2019). As outlined above, based on this dominance of REITs in the US market other organizational structures such as REOCs that are still dominant in Europe are underrepresented in research and offer a wide range of interesting questions that are worth pursuing.

Indeed, adding to existing research, we find in our research that a momentum strategy enables investors to outperform the market in the period between 1990-2023. Further, we find that for the whole period the momentum coefficient is significant at the 5% level. However, looking at the individual subperiods momentum coefficient is solely significant in one of the three subperiods, namely P2 where the financial markets could be described as distressed. The REOC momentum strategy generates outperforms the market in two of the three subperiods (P1, P2). Solely, in subperiod 3, where the normalized market returns are highest the momentum strategy fails to generate higher returns. This suggests that momentum investing can be a viable and profitable approach for market participants in the European real estate sector in periods where the market underperforms. We use the Carhart four factor model to test for significance of momentum. Furthermore, we perform both F-Tests and paired T-Tests to test for the difference between the individual subperiods. Lastly, we bootstrapped the momentum coefficient to increase the explanatory power of the factor and test for significant differences between the means of the distribution of the factor.

Looking at the findings above, this thesis aims to provide a comprehensive analysis of the results of momentum investing using REOCs between 1990-2023. Whilst this thesis relies mainly on data the findings of the thesis, especially the results of the subperiod 3 have been discussed with real estate professionals attempting to explain why for this subperiod the strategy failed to outperform the overall market. Our intention is to uncover factors driving the momentum phenomenon within REOCs, study its persistence across different market conditions, and derive implications for investors and market participants. This study will contribute to the understanding of an important submarket of the European real estate market, as well as the dynamics and the applicability of momentum-based investment strategies in this unique asset class.

The dissertation is divided into different sections. Firstly, the Literature Review summarizes previous publications relevant for this dissertation. It will closely examine the difference between REITs and REOCs and previous research published on the different structures and stress the importance of REOCs for research. Furthermore, it will explain the momentum effect in detail starting from its discovery and summarizing the main findings in the existing literature. For this thesis we have extended the focus beyond publications on the momentum effect itself and REOC structures but have widened it considerably to be able to increase the understanding of the deviations in momentum over the different periods investigated. Subsequently, section 3 will be introducing the Methodology used for this thesis. The Methodology discusses the data and variables used for the analysis of the momentum effect in REOCs starting from the data extraction, the process of data manipulation and giving detailed insights into the chronology of individual steps performed to achieve results. In the Results section the descriptive statistics, regression results and any additional tests will be introduced. Furthermore, there will be a high-level interpretation of the results in the section followed by a section on the Discussion. The Discussion will include a summary of the findings compare the results to those of other publications and comment on the limitations of this study together with suggestions for future research. The last section will be a Conclusion including final remarks and a concise summary of the paper.

2. Literature Review

The significance of real estate investments and the different behaviours of real estate stocks compared to other industry stocks has led to many publications focusing on the unique characteristics of the industry in the past. Especially direct real estate investments and REITs are often explored in existing literature with various differing research questions investigated. Equally, the momentum effect has been widely studied and documented in the financial literature, and numerous papers have contributed to the understanding of this phenomenon. This literature review will focus on the most prominent publications on the momentum effect, look at potential reasons for the prevalence of this anomaly and try to outline the motivations behind the approach chosen for this dissertation. Also, for a better understanding of the specificities of REOCs the differences between REITs and REOCs will be outlined extensively.

Although, the momentum effect in REOCs hat not yet been the subject of research in the past there are many publications on different industries from which this research gladly took its inspiration. The obvious starting point of this being the seminal paper of Jegadeesh and Titman (1993) where the market anomaly is described. Jegadeesh and Titman (1993) find that stocks with high past returns (winners) tend to continue outperforming those with low past returns (losers) in the short-term using different formation periods of 3 and 12 months and equally long holding periods between 1965 to 1989. Interestingly, the significance of these returns disappears over time and the profitability is seemingly not caused by systemic risk or delayed stock price reactions to common factors. While there was no obvious explanation for this momentum anomaly Jegadeesh and Titman (1993) assumed that the impact of "positive feedback traders" might be the root of this anomaly.

While this publication led the foundation of the work in this field, additional publications by Sheridan Titman, in example with Chui and Wei (2003a;2003b;2010) have equally been considered for this paper given their focus on REITs. Especially, Chui, Titman, and Wei (2003b), analysing intra-industry momentum in REITs. They find that for a period between 1983-1999 a REIT momentum strategy yields significant abnormal returns. Further, they find that for a post-1990 subperiod the momentum effect was much stronger than for the pre-1990 period. They chose the subperiods based on regulatory changes coming in effect in 1990 impacting REITs heavily. They conclude that due to the regulatory changes valuing a REIT has gotten significantly more difficult facilitating the presence of the overconfidence bias. (Daniel, Hirshleifer and Subrahmanyam,1998)

Equally, publications focussing on intra-industry comparisons such as Moskowitz and Grinblatt (1999) and several other publications with varying industry focus have had a big impact on this thesis, enabling us to refine the chosen approach continuously. Moskowitz and Grinblatt (1999) examine industry momentum and find that industry factors played a significant role in explaining the momentum effect. Their findings also provide a good basis for the research conducted in this study as they find that industry-specific factors contribute to momentum returns, implying that the momentum strategy should generate abnormal returns for REOCs given the returns generated by a REIT momentum strategy.

The data analysis is mainly based on two seminal publications. Firstly, Fama and French (1993) discuss various asset pricing anomalies. They argue that these anomalies can be largely explained by their three-factor model. This paper has been widely cited and has played a significant role in shaping the academic discourse around asset pricing anomalies. Thus, we will test how much of the variance of the REOC momentum strategy is captured by the Fama French 3 Factor model.

Next to this, we will look at an extension of the classic three-factor model, namely the Carhart four-factor model. Carhart (1996) extends the work of Fama and French (1993) and introduces a fourth factor to the model that incorporates a momentum (MOM), alongside the existing Fama French factors, market (Mkt-Rf), size (SMB) and value (HML). This paper has been influential in shaping the understanding of mutual fund performance and the use of multi-factor models in finance. Like the three-factor model, the four-factor model is a standard piece of literature and used to explain abnormal stock returns.

Initial research efforts have looked at the behaviour of REIT returns early. Titman and Warga (1986) have analysed risk-adjusted REIT performance using capital asset pricing models ("CAPM") and multi factor models such as the arbitrage pricing theory ("APT"). The CAPM thought up by

Sharpe (1964) and Lintner (1965) based on the Markowitz model (1959) assumes that investors choose a “mean-variance efficient” portfolio minimizing the variance of the portfolio given the expected return and vice versa (Fama and French, 2004). Titman and Warga (1986) have found that CAPM models perform better in predicting REIT returns, however, with the differences in investment performance being not significant due to the volatility of real estate investments.

With the discovery of the momentum effect by Jegadeesh and Titman (1993) research significantly changed as it was understood that simplistic models such as CAPM fail at capturing the variance in REIT returns. Therefore, we have not tested our returns using the CAPM model, but only using the Fama French three factor model and the Carhart four factor, which struggled to explain the variance in our momentum returns as we will show later.

Given the low explanatory power of conventional factor models more recent works such as Derwall et al. (2009) worked on finding alternative ways of capturing REIT momentum and explaining more variance in REIT returns. Instead of using the four-factor model they worked on the addition of a REIT momentum factor that adds incremental explanatory power to performance attribution models for REIT portfolios. The paper found that the introduction of a REIT momentum factor explains a significant share of abnormal returns that are earned by actively managed REITs better than conventional models. Given its explanatory power, the authors argued that the factor had a material impact on the cross-sectional comparisons of REIT performance.

This more recent research on the momentum effect in REITs can be seen as a complement to the existing research on the momentum effect in the industry conducted by Chui, Titman, and Wei (2003a), (2003b). Their finding that the momentum effect varies across different time periods is something that we aim at replicating for REOCs. Consequently, the previous research has also impacted the design of the subperiods. Especially, the period between 1990 and 1999 analysed by Chui, Titman, and Wei (2003b) has been investigated extensively and provided the basis of many influential publications on returns on real assets and listed real estate stocks. This is not only due to the regulatory changes in REITs but also due to the very strong appreciation of real asset prices over that period.

Extensive research has been conducted on the drivers of the price increase as well as the question of how the asset price increases are incorporated into REIT returns. A prominent piece of existing literature of examining the price increases in this period was published by Case and Shiller (2003) investigating the existence of housing price bubbles in the U.S. market following the rapid appreciation of house prices between 1995-2002. They did so by analysing regional home price indices, income, population changes, and construction costs. The authors employed a combination of different tests, such as time-series analysis, cross-sectional regressions, and survey data on homebuyers' expectations, to determine whether the observed price increases were fundamentally justified or driven by speculative behaviour. They found that – especially in certain coastal regions of the U.S. home price appreciation was only partially explained by changing fundamentals but primarily driven by expectations of future price appreciation.

The phenomenon of expected price appreciation driving the actual prices in the real estate market has not only been prevalent but in the U.S. but also in other parts of the world. One well known example is the “Lost Decade” in Japan also known as the "Japanese Bubble." The crisis was marked by a rapid increase in real estate and stock prices, followed by a sharp decline, leading to severe economic stagnation. Although, several factors such as loose monetary policy and financial deregulation played a strong role in the “Japanese Bubble” (Hoshi and Kashyap, 1999) and might have been unique specificities of this market, speculative behaviour resulting from expectations of continued price increases also facilitated the formation of a bubble.

However, moving away from the analysis of the existing literature on momentum, it is also vital to understand why we assume that REITs might behave differently than REOCs. To do so we want to give a comprehensive overview of the differences in structure of listed real estate companies. Also, we will dig into the history of listed real estate stocks and explain why the use REIT structures prevails in the US and is growing rapidly in Europe.

The behaviour of different real estate company structures has been a topic of interest for researchers in the past. Damodaran, John and Lui (1997) have analysed the impact of changing organizational forms in real estate with varying restrictiveness. They found that firms that underperform vis-à-vis to the sample moved to a more flexible organizational structure over time, increasing asset sales and investments by reducing dividends resulting in overall performance improvements. Firms moving towards a more restrictive structure exhibited larger free cash flows before the change and subsequently increased dividends, reducing free cash flows whilst improving profitability after the change. They also highlighted tax implications which might be a factor explaining performance differences between different structures. Translating this to the behaviour of REITs and REOCs it could be assumed that in periods of market turmoil REOCs outperform REITs due to the higher flexibility and more possibilities enabling adaptation to a changing market.

According to the European Real Estate Association (2019) the most prevalent organizational structure for listed real estate firms is REITs. In the United States there was a total of 249 listed real estate firms focussed on holding assets of which 189 were REITs and 60 were non-REITs as of December 2019. Translated to numbers the dominance of REITs is even more striking with a $1,266.67 bn. share of REIT market cap compared to $34.90 bn non-REIT market cap amounting to a total market cap of listed real estate of $1,301.57 bn (corresponding to 99.6% REITs).

The reasons for REIT dominance are clear as the structure offers tax advantages for both the REIT structure and shareholders. The guidelines for REIT eligibility published by the Securities and Exchange Commission ("SEC"), outline that: *"(1) A REIT must pay out at least 90% of its taxable income annually as shareholder dividends; (2) Invest at least 75% of its total assets in real estate assets and cash; (3) Derive at least 75% of its gross income from real estate related sources (4) Derive at least 95% of its gross income from such real estate sources (3) and dividends or interest from any source; and (6) have no more than 25% of its assets consist of non-qualifying securities or stock in taxable REIT subsidiaries"* (U.S. Securities and Exchange Commission, 2011).

At the same time in European market exhibited major differences when it comes to structure. In the European Union (incl. United Kingdom), the total market cap of listed real estate firms focussed on holding assets amounted to $ 513.25 bn of which only $243.55 bn (43%) were accounted for by REITs and the remaining $269.70 bn (57%) were non-REIT structures (EPRA, 2019). This difference is mainly due to the lack of coherent regulation on a European level. The European Real

Estate Association (EPRA) (2019) provides an analysis of the firm structure of listed real estate firms in Europe on a country level. While some countries – such as the UK, the Netherlands, and France – have a large majority of REITs several countries are underrepresented by REITs or lack listed REITs completely (Germany, Sweden and Austria). Furthermore, in countries with a small number of listed real estate companies REITs are often non-existent as there are simply no regulations putting REIT regimes in place. The most recent countries to adapt such REIT policies were Poland and Portugal in 2019. Other countries started adopting REIT regimes earlier in the late 2000s, with only one REIT existing in Europe in 1999 (Lorenz, 2020). Based on the significant share of REOCs in Europe and the literature outlining different behaviour of different organizational forms it seems intuitive to look closely at differences between REITs and REOCs. Indeed, some researchers have published articles on REIT and REOC behaviour. Delcoure and Dickens (2004) have shown that REITs and REOCs have different systematic risk levels despite similar underlying assets. More specifically, systematic risk generally is greater for REITs than REOCs. Further, there are also differences that stem from the real estate property type and regional location. Lorenz (2020) recently investigated underpricing in seasoned equity offerings (SEOs) between REITs and REOCs. He found that for REOCs SEOs are significantly underpriced compared to REITs.

3. Methodology

This section describes the data used to conduct the analysis for this study.

3.1. ***Real Estate Operating Companies***

For this dissertation, I have chosen the companies included in the Real Estate Operating Companies subset of the Global Industry Classification Standard (GICS) with the industry code 60201020 extracted from Refinitiv Eikon. After filtering for primary quotes solely and stocks that were listed between 1990 and 2023 a primary analysis was conducted. Following this analysis, it was decided to exclude all stocks not listed in Europe, as the quality of the returns of Real Estate Operating Companies in the other regions included unexplainable closing prices significantly increasing the volatility of the overall dataset and the comparability of the date.[1]

After the filters have been applied the resulting sample included 307 unique real estate operating companies. To ensure consistent data quality 3 further companies were excluded from the dataset based upon a final manual check of the individual stocks based on requirements such as a comparability of market capitalizations, total asset values, and extraordinarily high volatility of stock returns. The final sample thus includes 304 unique real estate operating companies across 35 countries.

The data used for this thesis was manipulated using Python. The stock returns have been extracted from Refinitiv Eikon. The Fama French three-factor model and Carhart four factor model data has been downloaded from the Kenneth French data library. Further data on REITs and REOCs has been extracted from leading data providers on real estate data such as Green Street or the

3.2 Data Analysis

In this study, I analysed the long-short returns of the stocks in my dataset over time to build long short portfolios based on the holding and formation periods. We use the returns of the *winners*, being the top 10th decile stocks, and the the *losers*, being the bottom 10th decile over a certain

[1] Furthermore, contrary to the US and Europe there is a lack of coherent information on differences in taxation between REITs and REOCs in the excluded regions. The absence of this information would have made the evaluation of the results more complex.

formation period and subsequently calculate the portfolio return buying the *winners* and selling the *losers*. The formation periods have been chosen in accordance with Jegadeesh and Titman (1993) varying between 3 to 12 months. The momentum effect for the existing sample of REOCs is most prevalent in the 12-month formation period excluding the most recent month in order to avoid the introduction of a reversal effect where stocks that exhibit a poor performance recently, but a long-term positive trend are mistakenly classified as momentum stocks. The exclusion of the most recent month was done adhering to the findings of George and Hwang (2005) that argued that an exclusion of the most recent month in the 12-month formation period enables capturing the true momentum effect increasing the effectiveness of the strategy which is also true for the chosen sample.

Thus, following the initial retrieval of the closing prices of the individual stocks in the chosen period from 1990 onwards and transforming the closing price to percentual returns the rolling 12 months excluding the most recent one was calculated.

Subsequently, a percentile was assigned to each stock for the rolling window. For the long-short returns the approach used to classify the *winners* and the *losers* respectively was a comparison of the top decile to the bottom decile of the returns of the REOCs included in dataset as this approach allows for the isolation of the most extreme performers in the dataset. Focusing on the stocks with the highest and lowest momentum, provides a clearer differentiation in performance and a better understanding of the underlying factors driving returns. This approach is in line with the approach of Jegadeesh and Titman (1993) as they also classified the top decile as *winners* and the bottom decile as *losers* in the in their paper.[2]

Alternatively, some studies have employed a different methodology, such as comparing the top and bottom quartiles. Asness, Moskowitz, and Pedersen (2013) used this approach to examine the value and momentum factors across multiple asset classes. Although this method still captures the momentum effect, given the sample and the underlying asset class analysed in this study it did not provide the same degree of differentiation in performance as the top and bottom decile comparison.

[2] In their paper "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency" the sample was composed of more than 1500 distinct stock included NYSE and AMEX for the period from 1965 to 1989.

Furthermore, the approach employed by Asness, Moskowitz, and Pedersen (2013) in their paper "Value and Momentum Everywhere," might have been used as they examined both the value and momentum factor across various asset classes, including individual stocks, country equity indices, government bonds, currencies, and commodities between 1971 through 2010. Using this approach, they were able to prove that both value and momentum factors generated positive and significant average returns across these asset classes and were negatively correlated with each other also concluding that these factors could not be explained by macroeconomic or business cycle risks, implying that they were pervasive and persistent across markets and time periods.

Nonetheless, given the unique characteristics of the real estate market, such as low liquidity, high transaction costs, and significant heterogeneity compared to other asset classes outlined by Gyourko and Keim (1992) we decided to employ the approach used by Jegadeesh and Titman (1993) as we believed that it would be more suitable for data exhibiting a wider dispersion in performance between the top and bottom performers, which the decile approach captures effectively potentially providing a clearer understanding of the drivers of the observed returns.

By including a larger set of securities in the analysis, the distinction between winners and losers becomes less pronounced, potentially leading to weaker results or a dilution of the momentum effect and further decreasing the overall performance of the strategy over the chosen period between 1990 and 2023.

Similarly, we have chosen to compare the results of a 3 to 12 month holding period of the derived long short portfolios. The research introduced in the literature review on the momentum effect believes that the anomaly is driven by factors such as gradual information diffusion and investor underreaction to new information. When news about a company's performance is released, it takes time for the market to fully process this information and adjust the stock price accordingly. This creates momentum in the stock's price as investors gradually incorporate the new information into their expectations. The momentum effect is strongest for holding periods of three to twelve months, but that it disappears or even reverses for holding periods of one month or less.

The table below illustrates the return profile of the long-short portfolio with a holding period of 3, 6, 9, and 12 months of the REOCs included in the dataset. Whilst all strategies generate positive average returns across all holding periods, with the highest mean excess return of 1.70% for the 6-, 9-, and 12-month strategies the 12-month strategy has the lowest volatility at 3.60%. Conversely, the 3-month strategy exhibits the highest volatility with a standard deviation of 7.80%.
For the further data analysis, we have decided to use the 12-month holding period. Given the similar returns compared to the other strategies and the lower volatility mentioned above the 12-month holding period has a higher Sharpe ratio[3] than the other holding periods.

Table 1: Excess Returns for different holding periods

	Excess_Returns 3_month	Excess_Returns 6_month	Excess_Returns 9_month	Excess_Returns 12_month
count	385	382	379	376
mean	1.63%	1.68%	1.68%	1.68%
std	7.77%	5.38%	4.23%	3.56%
min	-22.20%	-17.60%	-12.43%	-11.30%
25%	-3.08%	-1.32%	-0.67%	-0.30%
50%	1.33%	1.42%	1.18%	1.50%
75%	5.37%	4.45%	4.23%	3.72%
max	28.95%	23.68%	21.07%	15.79%
Skewness	0.40	0.17	0.26	0.33
Kurtosis	1.19	1.76	2.31	2.20
Sharpe Ratio	0.21	0.31	0.40	0.47

For the holding periods of one month or less, existing research argues that the news about a company's performance is already fully incorporated into the stock price, and any further price changes are likely to be due to noise or short-term fluctuations rather than new information. As a result, the momentum effect disappears or even reverses for very short holding periods. For our dataset we further examined the returns for holding periods longer than 12-months and found that the highest mean excess return is generated for a holding period of 27-months at 1.72%, which might support the idea that the reversal of the momentum effect might be slower compared to asset classes based on the fact that the returns of the REOCs are factored into the property appraisals

[3]The Sharpe ratio measures the risk-adjusted return of an investment. It is calculated as the excess return of an investment or portfolio over the risk-free rate divided by its standard deviation. A higher Sharpe ratio indicates better risk-adjusted returns, while a lower Sharpe ratio indicates lower risk-adjusted returns.

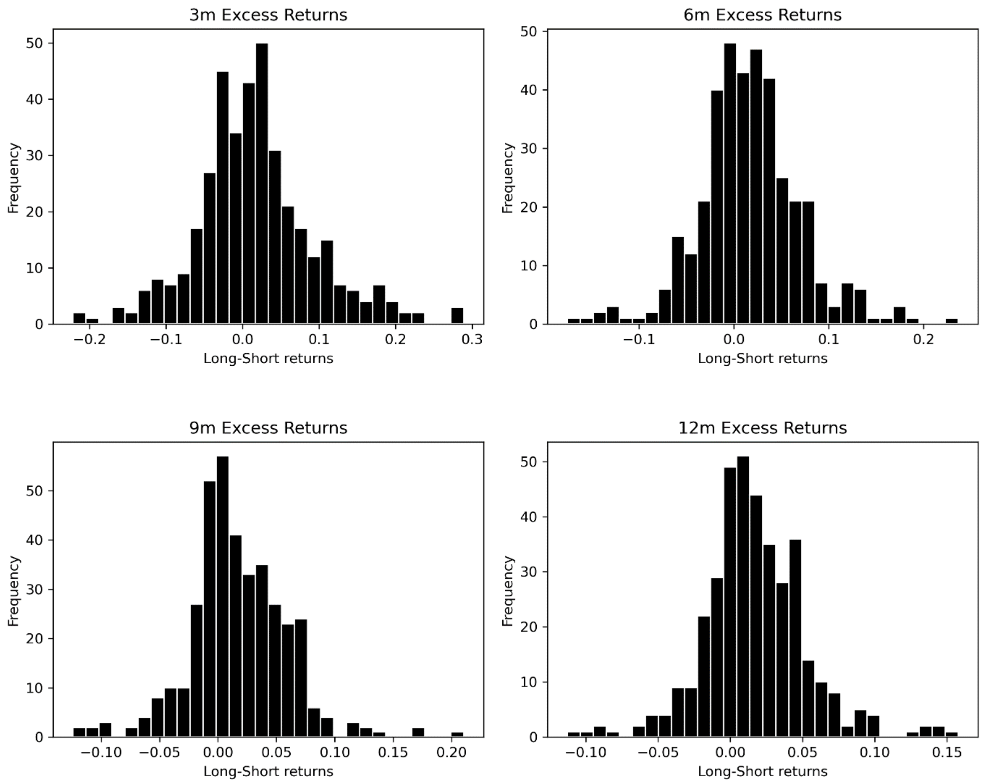
improving the fundamentals of the underlying stock (Gyorku and Keim, 1992). If this were the case one could also assume that contrary to what Asness, Moskowitz, and Pedersen (2013) found macroeconomic, or business cycle risks could play a more important role for the real estate industry compared to the other asset classes investigated by the authors.

However, based on the existing research we have decided to not include this holding period, primarily due to the constraints of the existing literature and the scope of the study. Holding periods ranging from 3 to 12 months, provide a robust foundation for comparison and analysis. Extending the holding period beyond 12 months would have required additional data, time, and resources, which were not feasible within the scope of our study.

However, our findings suggest that a holding period of 27 months generated the highest excess returns, indicating the potential for further investigation in future research. By exploring longer holding periods, researchers could gain a deeper understanding of the underlying factors driving momentum strategies and their performance. The extension of the holding period in future studies could also shed light on potential anomalies or market inefficiencies not captured in the current literature on the momentum effect of REOCs and REITs potentially related to the illiquid nature of the asset.

For a deeper understanding of the excess returns, we utilized the histogram of excess returns over time. It is visible that with an increase in holding period there is a decrease in extremity of outliers in the data. Furthermore, it becomes clearly visible that for the 6 months holding period the skew is almost eliminated and the data is almost perfectly normal in its distribution. Similarly, it is visible that the 9 months holding period exhibits the highest kurtosis with the peak of the returns at 0%.

Table 2: Histogram of Excess Return



For a further analysis of the data, we decided to look at the excess returns of our long short portfolio for every year included in the dataset. The appendix **5.1** shows the excess returns and their corresponding standard deviations for real estate operating companies over the various periods (3-month, 6-month, 9-month, and 12-month) between 1991 and 2021. Looking at the trend of returns and volatility over time there are several possible reasons behind them.

By investigating the excess returns and the standard deviation for each year, we can get an idea of the overall development of the momentum returns allowing us to examine the stability and robustness of this effect over time. What we see is that the excess returns and volatility of real estate operating companies have experienced significant changes over time, with notable fluctuations during specific periods a few are outlined below.

Firstly, in 1999, both the excess returns and volatility reached their highest levels across all periods, with 3-month returns peaking at 8.76% and standard deviations at 9.28%. This can be attributed to the booming economy during the late 1990s, which had a positive impact on the real estate market. The strong excess returns of the long-short portfolio could potentially indicate similar behaviour to REITs, discussed in Chui, Titman, and Wei (2003b). The strong performance goes hand in hand with the strong increase in real estate prices in that period causing research into pricing bubbles. (Case and Shiller, 2003)

Conversely, in 2009, the excess returns were at their lowest, with 3-month returns dropping to -8.97%, accompanied by a relatively high volatility of 6.11%. This was a result of the 2008 financial crisis, which had a substantial impact on the real estate market and led to high volatility and low returns.

In 2016, both excess returns and volatility were high, particularly for the 9-month and 12-month periods. The 12-month excess return reached 11.69%, with a standard deviation of 2.45%. Factors such as an improving economy, low interest rates, and increasing demand for real estate could have contributed to these high returns and volatility.

The early 2010s saw relatively low excess returns coupled with high volatility. For instance, in 2013, the 3-month excess return was 2.45%, with a standard deviation of 10.66%. This might be attributed to the slow recovery of the real estate market following the 2008 financial crisis, as well as uncertainties surrounding economic growth.

These various periods illustrate the dynamic nature of the returns of REOCs. It can be said that the excess returns and volatility of the REOC long-short portfolios over time seems to be strongly influenced by macroeconomic factors, including economic growth, interest rates, and market demand. Periods of high returns and volatility coincide with economic booms, while periods of low returns and high volatility reflect economic downturns or slow recoveries clearly visible in the data.

Based on the results we decided to proceed as follows. We will initially focus on the entire period in the sample, namely, 1990-2023 and see to what extent the momentum effect in REOCs is captured by the Fama French three-factor model as well as the Carhart four-factor model. Subsequently, the overall period will be divided in three subperiods of equal length being:

P1 (1991-2000): The first period covers the early years of the real estate market data, capturing the market fluctuations in the 1990s, including the rise of the technology sector leading up to the start of the market downturn related to the dot-com bubble.

P2 (2001-2010): The second period encompasses the early 2000s, the dot-com bubble burst, followed by the recovery and growth of the real estate market in the mid-2000s leading up to the 2008 financial crisis.

P3 (2011-2020): This period focuses on the real estate market's performance after the financial crisis, including the effects of low interest rates, economic recovery, and other market drivers. The period includes events like the European sovereign debt crisis, the Brexit referendum and the global COVID-19 pandemic, which had a profound impact on the real estate market in 2020.

These divisions result in three subperiods of 10 years each, providing a comprehensive overview of the real estate market's momentum effect during different economic environments. Furthermore, by using three similarly long periods we can generate additional insights whilst excluding years will less explanatory power.[4]

Following the analysis of the total dataset we will regress the individual periods against the chosen factor models. To check for the significance of the momentum effect over time, the periods will then be compared, and the significance of differences will be tested using an F-Test and subsequently we will bootstrap the momentum coefficient to further look into the prevalence of momentum in the three subperiods.

[4] The years with less explanatory power are 1990 due to a very low number of REOC listings. Furthermore 2022 and 2023 are rightfully excluded as 12 month holding period can not be included. The last return data is available for the most recent data minus the holding period.

4. Results

To have a comprehensive view of the results of our thesis we will start by looking at the results of the entire dataset. We do this for the sake of legibility and to visualize the thought process of this dissertation. Therefore, we will look at the Fama French three factor model regression, the Carhart four factor regression and then a closer look of the individual results.

4.1. Results of the entire period

As discussed, for a review of the results we will start by looking at the results of the Fama French three factor model for the whole period in the dataset.

The results, shown in *Table 3* below, indicate that the Fama French three factor model is not a suitable model to analyse the returns of a long-short portfolio illustrated by the low R-squared of 0.018, indicating that only 1.8% of the variation in the excess long-short strategy returns is explained by the model.

The F-statistic value is 2.310, with a p-value of 0.0760. This p-value is greater than the significance level of 0.05, suggesting that we fail to reject the null hypothesis that all the coefficients in the model are zero. Whilst the F-statistic is significant at a 10% level the model does not provide significant explanatory power for the excess long-short strategy returns.

Looking at the individual coefficients and their p-values, we find that the constant(alpha) is 0.0197. Thus, when all factors are zero, the expected excess return of the long-short strategy is 1.97%. The coefficient for the market excess return (Mkt-Rf) is -0.3506, with a p-value of 0.039, also statistically significant at the 5% level indicating that as the market excess return increases, the excess long-short strategy return decreases.

The remaining factors for size (SMB) and value (HML) are both not statistically significant with p-values of 0.475 and 0.141 respectively. This suggests that there is no significant relationship between the either of them and the long-short strategy return.

Table 3:Regression Results – Fama French three-factor model

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      Excess_Long-Short   R-squared:                       0.020
Model:                            OLS   Adj. R-squared:                  0.009
Method:                 Least Squares   F-statistic:                     1.857
Date:                Mon, 01 May 2023   Prob (F-statistic):              0.137
Time:                        23:57:35   Log-Likelihood:                 151.34
No. Observations:                 276   AIC:                            -294.7
Df Residuals:                     272   BIC:                            -280.2
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0252      0.009      2.914      0.004       0.008       0.042
Mkt-RF        -0.3769      0.194     -1.943      0.053      -0.759       0.005
SMB           -0.2159      0.277     -0.780      0.436      -0.761       0.329
HML           -0.2374      0.267     -0.890      0.374      -0.762       0.288
==============================================================================
Omnibus:                       72.013   Durbin-Watson:                   2.104
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              401.895
Skew:                           0.911   Prob(JB):                     5.37e-88
Kurtosis:                       8.624   Cond. No.                         36.4
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Despite the overall results being disappointing what is interesting is the negative relationship of the market excess return that is somewhat surprising, as one might expect a positive relationship between market performance and a long-short strategy.

Overall, as expected and indicated in the existing literature, the Fama-French 3-factor model doesn't fit the data well. However, to analyse the overall fit of the model for REOCs we have also regressed the excess returns of every decile using the method in *Appendix 3.* The analysis outlines that while the R-squared is relatively low, the highest achieved for the ninth decile at 16%, market returns are significant at a 1% level in for six out of the ten deciles, size in two out of ten deciles and value only for one of the deciles providing comfort into the data manipulation done.

Following the Fama French three factor model, we have looked at the Carhart four-factor model. What we find in the overall significance only increased slightly to an R-squared of 0.035. Nonetheless, the F-statistic value is 3.436, with a p-value of 0.0089. This p-value is lower than the 5% significance level and even significant at 1%, suggesting that we can comfortably reject the null hypothesis that all the coefficients in the model are zero. Thus, we see that there is significant explanatory power of the model for the momentum strategy returns.

For the individual coefficients and their p-values, we find that the constant(alpha) is 0.0166. Similarly, to the Fama French model this means that when all factors are zero, the expected excess return of the long-short strategy is 1.66%. The coefficient for the market excess return (Mkt-Rf) is negative as well at -0.2043, but not significant with a p-value of 0.250 The factors for size (SMB) and value (HML) are both not statistically significant with p-values of 0.431 and 0.403 respectively and to be neglected.

Interestingly, we find that the momentum factor (MOM) is significant both at a 5% significance level and even at a 1% level, implying that there is momentum in the returns of our long-short strategy on REOCs. The momentum coefficient is positive at 0.4221 whilst the coefficient for market returns is again negative at -0.2043.

Table 4: Regression Results – Carhart four-factor model

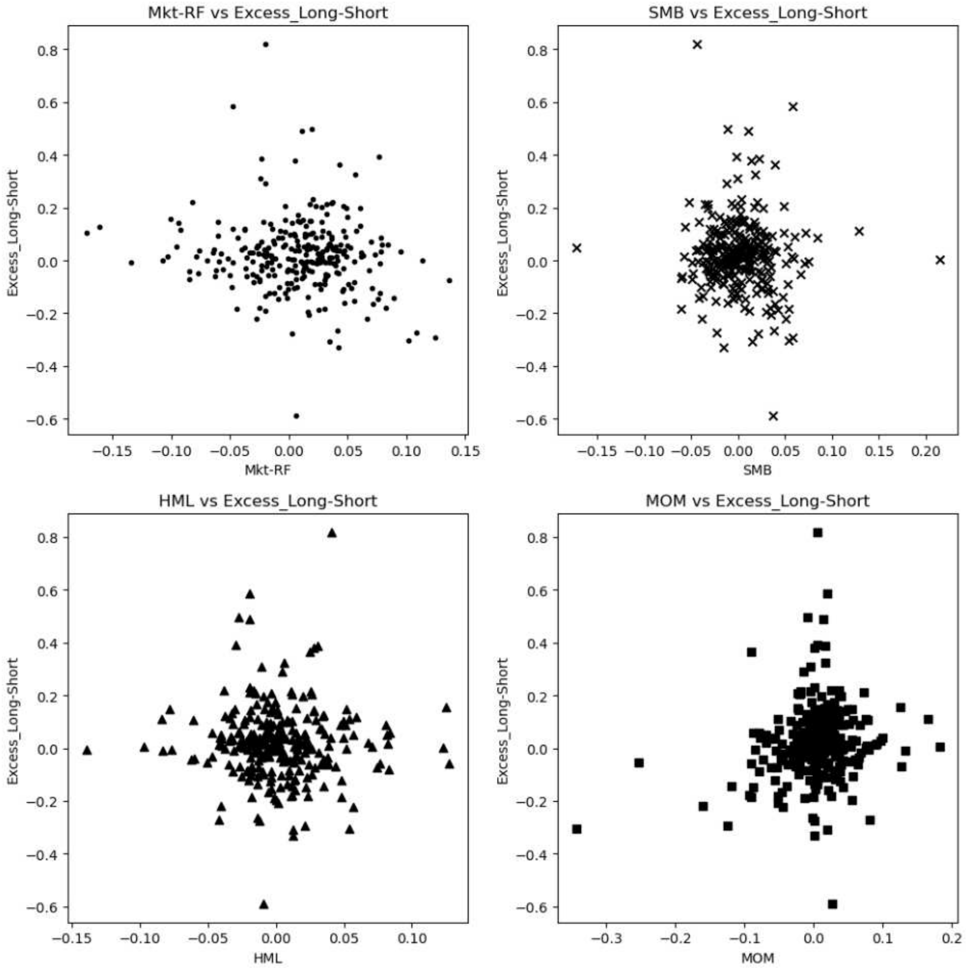
```
                            OLS Regression Results
==============================================================================
Dep. Variable:      Excess_Long-Short   R-squared:                       0.035
Model:                            OLS   Adj. R-squared:                  0.025
Method:                 Least Squares   F-statistic:                     3.436
Date:                Sat, 06 May 2023   Prob (F-statistic):            0.00893
Time:                        11:35:45   Log-Likelihood:                 209.20
No. Observations:                 386   AIC:                            -408.4
Df Residuals:                     381   BIC:                            -388.6
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0166      0.007      2.236      0.026       0.002       0.031
Mkt-RF        -0.2043      0.177     -1.151      0.250      -0.553       0.145
SMB           -0.1897      0.240     -0.789      0.431      -0.662       0.283
HML           -0.1953      0.233     -0.837      0.403      -0.654       0.264
MOM            0.4221      0.163      2.590      0.010       0.102       0.742
==============================================================================
Omnibus:                      102.999   Durbin-Watson:                   2.160
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              610.020
Skew:                           0.980   Prob(JB):                    3.43e-133
Kurtosis:                       8.838   Cond. No.                         36.2
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified
```

Overall, the relevance of the underlying research question is supported by the regression results. The regression analysis indicates that the momentum factor has a positive and statistically significant relationship with the excess returns of the long-short momentum strategy. The fact that the model only explains a relatively small proportion of the variance in the excess returns is supported by the existing literature and could be tackled by introducing additional variable such as a REOC momentum factor, which is outside of the scope of the current project, potentially adding autocorrelation, not present here shown by the Durbin-Watson test.

Similarly, to the approach outlined for the Fama French three factor model we looked at every decile and regressed the excess returns of every decile. The results in *Appendix 4* show that for the deciles the Carhart four factor model is significantly more accurate in predicting excess returns. The R-squares outline this with the highest ones being 0.1940 for Portfolio 9 and 0.1675 for the bottom Portfolio 10. The momentum factor (MOM) was significant for those two deciles. The market factor was significant at a 1% level for 6 out of the deciles. The significance of the other factors is negligible, identical to the initial evaluation using the three factor model.

To visualize and check our regression results we have employed a scatter plots of the independent variables Mkt-RF, SMB, HML, and MOM against the excess returns of the long-short strategy reveal the relationship between these factors and the strategy's performance. The plots show a no visible relationship between SMB, and HML factors and the excess returns, which is in line with our findings. For the Market-Rf factor while a negative relationship is expected, the scatterplot is not able to visualize this, solely the fact that the returns are heavily dispersed. A visibly positive relationship can solely be observed for the MOM factor.

Table 5: Scatter plot REOC Portfolios Excess Long Short Returns, 1990-2022



To sum up, we have established that momentum indeed is prevalent in our data using the Carhart four factor model. However, there are limitations that will be discussed at a later point within this dissertation. Furthermore, there are points worth exploring further such as the behaviour within the different subperiods chosen.

4.2. Results within the individual periods

As outlined above the three periods we have chosen are composed of ten years and therefore 120 observations each starting in 1991. We used those equally long periods as the subperiods encompass very specific macroeconomic events. Period 1 (1991-2000) could be considered as a boom period. Period 2 (2001-2010) is a period of crisis, starting with the bursting of the “dotcom” bubble and ending with the subprime mortgage crisis. Period 3 (2011-2020) could be considered as recovery period, which also exhibited massive growth.

Initially, we have decided to run the regressions we ran for the whole period again for the individual subperiods. The results of the Fama French three factor regression of the individual periods have been added as Appendix 5. The OLS regression results indicate that the relationship between the Fama-French factors and the excess long-short return is not consistent across the subperiods. Size (SMB) and value (HML) factors are not statistically significant in the subperiods, which confirm the limited predictive power of the factors for the excess long-short return.

Most notably, the second subperiod has a higher R-squared compared to the other subperiods, indicating that the Fama-French factors explain a larger portion of the variance in the excess long-short return. The market factor is both negative and statistically significant, suggesting that the long-short strategy tends to underperform when the overall market performs well.

To investigate this observation, we ran the OLS regression on the Carhart four factor model summarized below in *Table 6*.

Table 6: Regression Results - Carhart four factor model - Subperiods

	Periods		
	P1	P2	P3
R-squared	0.0125	0.1246	0.0182
Alpha	0.0286	0.0091	0.0194
Mkt-RF Coef.	-0.3332	-0.2812	0.0010
Mkt-RF p-value	0.3543	0.3452	0.9982
SMB Coef.	0.0558	-0.4161	-0.8543
SMB p-value	0.8784	0.3632	0.2244
HML Coef.	-0.4140	-0.4100	0.1625
HML p-value	0.4147	0.2862	0.8045
MOM Coef.	-0.0242	0.5183	0.1750
MOM p-value	0.9450	0.0196	0.7447

The analysis of the Carhart four-factor model across different periods highlights the varying significance of the momentum factor and the goodness of fit of the model over time. Focusing on the p-values of the momentum factor, we observe that the momentum factor is statistically significant during the total period (p-value of 0.010, significant at the 1% level) and P2 (p-value of 0.020, significant at the 5% level). Momentum was not significant during P1 (p-value of 0.945) and P3 (p-value of 0.745).

Regarding the goodness of fit, the R-squared values implies that the highest goodness of fit is observed during P2 (R-squared of 0.125). P1 has an R-squared of 0.012 and P3 has an R-squared of 0.018. The R-squared value for the total period is 0.035, indicating that the explanatory power is significantly higher in P2 compared to the other subperiods.

The results establish the following. Momentum exists during the total period and P2 but is far from being statistically significant in P1 and P3.

To compare the variances or variability of the individual periods we conducted a F-test. The result of our ANOVA test is illustrated below in *Table 7*. The p-value is 0.3615 not significant at a 5% level, thus we cannot reject the null hypothesis that the variance across subperiods is significantly different.

Consequently, we also ran a paired t-test to compare the means of the individual subperiods to determine if there is a significant difference between them. The pairwise t-tests do not provide evidence for statistically significant differences in the excess returns between any of the three subperiods (P1, P2, and P3).

Table 7: F-Test of the subperiods

Test	Value
F-statistic	1.0203
p-value	0.3615

Table 8: T-Test of the subperiods

Comparison	t-statistic	p-value
P1 vs P2	1.0400	0.2994
P1 vs P3	0.2067	0.8365
P2 vs P3	-0.7274	0.4670

While these results show that the difference of mean and variance within the individual subperiods is not statistically significant, we wanted to magnify the momentum coefficient. In order to do so we attempted bootstrapping the momentum (MOM) coefficient to estimate the sampling distribution of the statistic and to obtain more accurate estimates of the standard errors, confidence intervals, and p-values.

Bootstrapping is a resampling technique that helps to assess the uncertainty and variability of a statistic, like the MOM coefficient, by generating multiple samples from the original data with replacement.

In this specific case, bootstrapping is used to obtain a more robust estimation of the MOM coefficients for the three subperiods (P1, P2, and P3). By resampling the data with replacement, the bootstrapping process creates a new set of samples for each subperiod and recalculates the MOM coefficients for each of these samples. This process is repeated a certain number of times (50 iterations in this case). Following the resampling of the bootstrapped momentum coefficient the data was analysed.

Table 9: T-Test of bootstrapped momentum coefficient of the subperiods

Comparison	t_statistic	p_value
P1 vs P2	-6.9796	0.0000
P1 vs P3	-0.6186	0.5376
P2 vs P3	6.6501	0.0000

Looking at the subperiods P1 vs P2 we find that there is a statistically significant difference between the MOM coefficients of subperiods. The p-value is significant at a 1% level, with the negative t-statistic suggesting that the momentum coefficient for P1 is smaller than that for P2. For the subperiods P2 vs P3 the p-value is also significant at a 1% level. Further, the positive t-statistic suggests that the momentum coefficient for P2 is larger than that for P3.

Lastly, for P1 vs P3 there is no statistically significant difference between the momentum coefficients of subperiods P1 and P3, at a 5% level. However, at a 10% level this factor would be significant.

The bootstrapping process provides more accurate and robust estimates of the MOM coefficients allowing for a meaningful comparison across subperiods.

5. Discussion

In this thesis, we aimed to investigate the momentum effect in European REOC stock returns between 1990-2023 and three distinct 10-year sub-periods from 1991 onwards. Our main objective was to examine whether the momentum is prevalent in the REOC returns and to investigate if the momentum effect varies across these sub-periods, which could potentially reflect changes in market conditions or investor behaviour.

Our findings indicate significant differences in the prevalence of momentum over time, as revealed by the pairwise t-tests, ANOVA (F-test), and the bootstrapping analysis that indicates significant difference between sub-periods P1 and P2, as well as between P2 and P3. This suggests that the momentum effect is not consistent throughout the entire period under study.

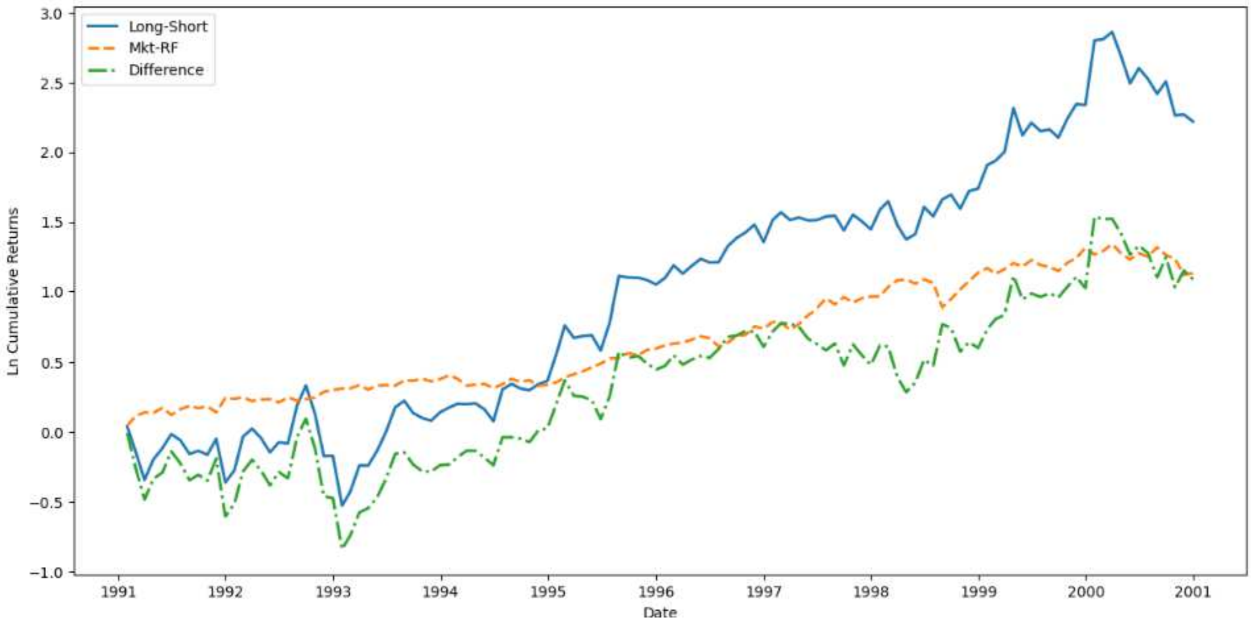
One possible explanation for these findings is that changes in market conditions, such as economic cycles or shifts in investor sentiment, could have influenced the strength of the momentum effect.

In addition to market conditions, investor behaviour could also play a role in the observed differences in momentum coefficients. For instance, if investor sentiment changes and investors become more risk-averse during certain periods, it could lead to a reduced momentum effect as investors become less inclined to follow trends in stock returns. On the other hand, periods of increased risk tolerance might result in stronger momentum effects, as investors chase higher returns.

In our analysis, the results indicate that the momentum effect is more significant in periods where the market performs poorly, specifically during the "bust" period (P2). This observation is derived from the significant p-value of the momentum coefficient in P2. This finding suggests that the momentum effect may be more pronounced during market downturns, which has important implications for investors and portfolio managers.

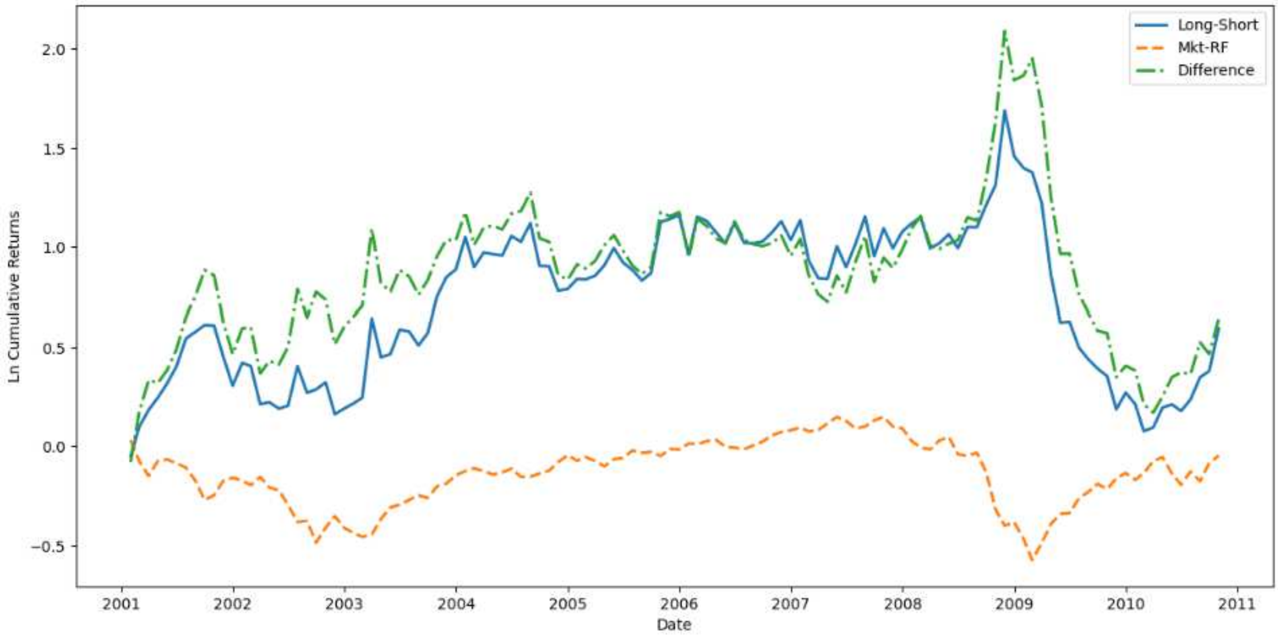
Nonetheless, it is essential that we take the results with a grain of salt. This is because if we look at the general performance of the long-short strategy throughout the period, we find that in the first period P1 the long-short strategy outperformed the market consistently and further analysis into the individual deciles showed that the returns of the bottom decile were consistently negative, while the top decile outperformed the market heavily. The results look like a textbook application of the momentum effect and are somewhat similar to those referred to generated by Chui, Titman and Wei in 2003. Looking at the performance, in period 1, the momentum strategy generates the highest mean return of 2.7%.

Table 10: Natural Log Cumulative Returns for Period 1



In the second period we find that while the outperformance of the long-short strategy was significant during the first years, after 2009 the outperformance disappeared. Looking into the detailed performance of the individual deciles we find that the strategy was particularly strong after the start of the subprime crisis. Whilst the top decile only exhibited small but steady losses, the returns of the bottom deciles turned significantly negative boosting the returns of the strategy. However, following the initial jump in long-short returns the bottom decile returns recovered much stronger than those of the top decile, resulting in negative long-short returns between 2009 and 2010, illustrated in *Table 11.* The reversal and subsequent underperformance of the strategy from 2009 onwards makes the use of the momentum strategy less desirable. Overall, the mean return over the entire period is at 1.24%, however, this period offers the lowest risk-adjusted return at 0.1. The results are extremely disappointing given that the existence of momentum was proven in this period.

Table 11: Natural Log Cumulative Returns for Period 2



We have also looked at the third period, which from the overall characteristics looks somewhat similar to the first one. However, contrary to the other periods, the momentum strategy was not able to generate excess returns in this period. Looking into the returns of the individual deciles we make a very interesting finding, namely, that for the third period both the top and the bottom decile outperformed the market resulting in a overall underperformance of the strategy.

Table 12: Natural Log Cumulative Returns for Period 3

Especially, our findings in P3 imply that the momentum strategy could be far from ideal in a very strong market environment. There are several potential reasons that might help to explain the weaker overall performance of the momentum strategy in periods of strong market performance (P3).

In strong market conditions, investors may be more prone to profit-taking or rebalancing their portfolios, which can lead to reversals in stock price trends. This can reduce the effectiveness of the momentum strategy, as it relies on the persistence of trends (Jegadeesh & Titman, 1993). Although, we tried to control for reversals by excluding the most recent month in our formation period, it might explain the results presented above.

Looking at the significance of momentum during periods of weaker overall market performance (P2), we find several potential reasons in the existing literature. Looking at market downturns, Hirshleifer (2001) indicated that they are often characterized by higher levels of uncertainty and volatility. These conditions may make it more difficult for investors to process information efficiently, leading to more significant price discrepancies and stronger momentum effects. As investors slowly react to new information, the stock prices might exhibit a stronger momentum during these periods, especially given the illiquid nature of the asset and the extremely high dependency on changes in the valuations of the underlying properties. Further, during market downturns, investors might become more risk-averse, leading them to rely more heavily on past stock price trends to make investment decisions. This behaviour could reinforce the momentum effect, as investors are more likely to follow the trend of stock prices when the market is performing poorly (Chui, Titman & Wei, 2003b; Jegadeesh & Titman, 1993).

Next to this, the fundamental factors in behavioural economics such as loss aversion and herding behaviour might play a role looking at the prevalence of momentum in contracting markets. Panic-selling, associated with loss aversion, which is the tendency to be more sensitive to losses than to gains might also play a role (Kahneman & Tversky, 1979). During market downturns, this psychological bias could lead investors to sell their losing stocks more quickly, while holding on to their winners (Odean, 1998). This behavior can create a momentum effect, as the stocks that have already performed poorly continue to underperform, while the winners continue to outperform. Additionally, herding behavior, or the tendency of investors to follow the actions of others, can exacerbate the momentum effect in such periods (Hirshleifer, 2001).

However, it is crucial to acknowledge the limitations of this research. Firstly, this study focused on REOCs, a very specific sub-industry of the real estate market, with a focus on the European market. Given the fact that the market for listed stocks in the real estate industry grew significantly slower in Europe compared to the US and the dataset is further limited by European REIT regimes the sample is not ideal in terms of size or characteristics of the included firms. Thus, we have also not been able to look closer at potentially interesting factors such as the impact of the underlying asset type on the prevalence of momentum. Overall, the small sample of European REOCs limits the generalizability of the findings. Furthermore, the R-squared values of our models are consistently quite low across all models, indicating that a significant proportion of the variation in returns remains unexplained, which might be mitigated using alternative factor models for future research.

The low explanatory power might also jeopardize the overall results of the study. Specifically, the fact that in the first period, where the momentum strategy performed best, the factor was not close to being significant needs to be pointed out.

Further limitations must include the fact that we focus on specific subperiods and relied on bootstrapping the momentum coefficients to understand the difference between the momentum coefficient between periods.

Nonetheless, our findings contribute to the existing literature on REOCs, which are a field within the real estate sector that has been neglected given the higher importance of REITs outside of Europe. It also contributes to the existing research by further investigating the momentum effect by providing evidence of its variability across different sub-periods. Previous studies – such as Chui, Titman & Wei (2003b) - have reported similar results regarding the persistence and magnitude of the momentum effect in REITs over time. Nonetheless, one might argue based on our results that their observations were not based on regulatory changes facilitating overconfidence but rather due to changes in the market environment.

Future research could extend the analysis to different timeframes and market conditions or explore alternative methodologies to compile the long-short portfolio assessing the strength of the momentum effect in REOCs. Future research could especially focus on larger buckets potentially helping in reducing volatility improving the risk-adjusted returns which were very poor in our study. The research could also be further refined to analyse the characteristics of winners and losers within the subperiods. The observed differences in momentum coefficients have important implications for investors and portfolio managers. Understanding the factors that drive the momentum effect and its variability can help investors make more informed decisions about their investment strategies.

6. Conclusion

In conclusion, this thesis aimed to investigate the momentum effect across different market conditions and assess its prevalence during periods of market turbulence. The research focused on three subperiods, representing a boom, a bust, and a recovery phase, and examined the momentum coefficients for each of these periods.

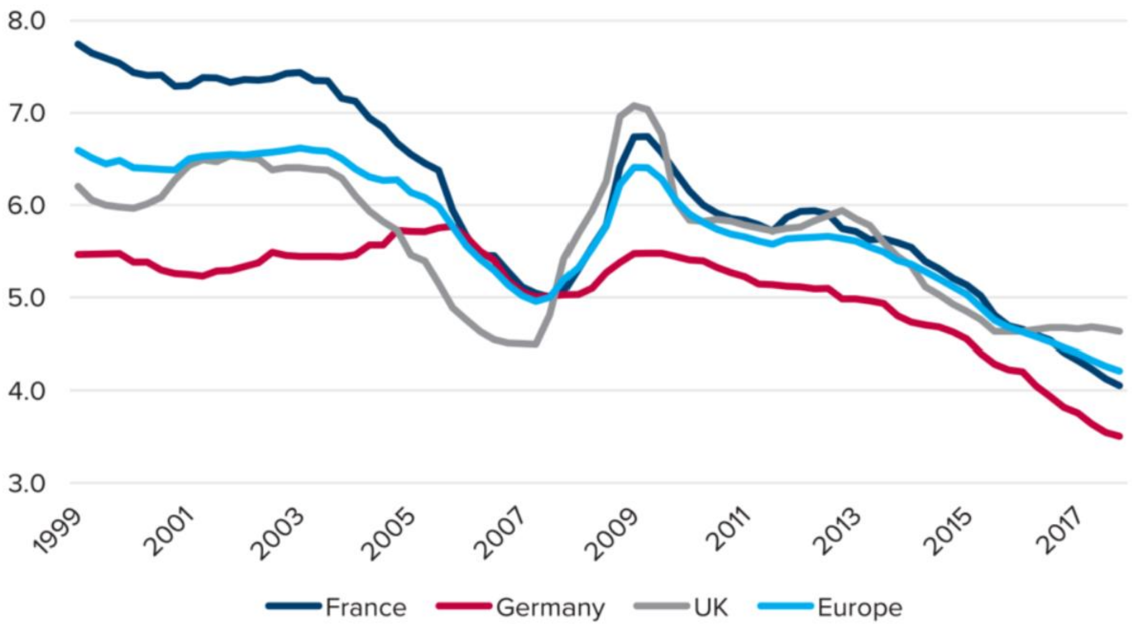
The findings suggest that using REOC returns a momentum strategy generates excess returns in the period between 1990-2023. We find that the strategy performed best in the first period from 1991 to

2000. Further, with the exception of the third period the strategy is able to outperform the market. While we are able to prove the existence of momentum in the overall sample using the Carhart four factor model, we fail to prove its existence in two of the three subperiods. Our findings indicate that momentum is more prevalent during the bust period (Period 2). Specifically, the momentum coefficient was statistically significant in Period 2, while it was not significant in Periods 1 and 3.

These results incline to make the argument that momentum strategies are most visible during market downturns. We explore possible reasons for this, namely behavioural biases, risk aversion or market inefficiency.

We have also looked at potential reasons, why for period 3, no excess returns have been generated. The fact that even the losers outperformed the market in the period indicates the force of capital appreciations and yield compressions in the last years. Looking at the recovery of the real estate market starting in 2010 following the subprime mortgage lending crisis we have seen constant compression of the yields in Europe across all asset classes seen in the *Table 13* below.

Table 13: All property yields in Europe – 1999-2018



Sources: CBRE & AEW Research 2018

This historically unparalleled yield compression will have resulted in increasing capital value reflected in the REOCs fundamentals. Therefore, we believe that the increases in book values caused even the historical losers to outperform the overall market due to valuation effects of the underlying fuelling believes in further capital appreciation. Applying this thought and discussing with industry professionals our results in period 3 are largely supported in the sense that both the speed of positive changes in the asset values and the willingness of market participants to invest at extremely high capital values was extraordinary.

Despite the low explanatory power of the models employed by us, we believe these findings to be relevant for the REOCs market which is largely neglected by researchers. Understanding the factors that influence REOC returns can help investors and portfolio managers make better-informed decisions about their investment strategies and might encourage practitioners to consider implementing momentum strategies during periods of market distress, to potentially enhance their investment returns.

Given the big research gap, there are many interesting angles that would be worth exploring. Looking at our returns specifically studies could investigate the underlying causes of the significance of the momentum factor during the bust period, further examining the role of behavioural biases, investor sentiment, or liquidity constraints driving momentum. Also, follow-up research on the paper of Case and Shiller (2003) might be valuable given the behaviour of REOC returns in period 3. Lastly, we firmly believe that our approach can likely be refined further, my increasing the size of the buckets, or altering the holding and formation period in an attempt to increase the explanatory power of our research or reach different conclusions on the success of a momentum strategy in REOCs.

In closing, this thesis has shed light on the momentum effect and REOC returns. We have shown that the dynamics of financial markets drive the momentum strategy performance, and that momentum is not equally prevalent throughout different periods.

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8. Appendix

8.1. Summary of excess return over time

	Excess_Returns 3_month	Excess_Returns 6_month	Excess_Returns 9_month	Excess_Returns 12_month
1991	1.02% (6.53%)	0.85% (3.08%)	1.55% (2.59%)	1.71% (2.02%)
1992	-1.14% (10.78%)	0.00% (4.98%)	0.56% (3.10%)	1.01% (1.84%)
1993	5.15% (6.17%)	3.73% (4.56%)	2.90% (2.60%)	2.65% (1.79%)
1994	4.21% (5.92%)	4.36% (1.96%)	4.96% (2.80%)	5.43% (1.42%)
1995	4.30% (7.61%)	4.62% (3.14%)	3.89% (2.14%)	3.57% (1.28%)
1996	3.18% (2.31%)	2.81% (1.35%)	2.38% (1.20%)	1.92% (1.17%)
1997	0.18% (1.95%)	-0.12% (1.62%)	0.33% (1.53%)	0.69% (1.24%)
1998	3.40% (5.85%)	5.16% (3.69%)	5.04% (2.52%)	5.22% (1.59%)
1999	8.76% (9.28%)	6.52% (4.88%)	5.69% (2.04%)	4.46% (2.99%)
2000	-4.13% (4.59%)	-2.21% (4.63%)	-0.55% (4.86%)	0.49% (3.26%)
2001	2.49% (6.83%)	0.91% (5.64%)	0.05% (3.45%)	-0.33% (1.99%)
2002	0.78% (6.86%)	2.22% (3.72%)	2.47% (2.76%)	3.39% (2.53%)
2003	6.09% (4.92%)	5.31% (2.71%)	4.99% (2.10%)	3.85% (2.52%)
2004	-0.82% (4.40%)	-0.51% (2.67%)	-0.74% (0.86%)	0.15% (1.78%)
2005	2.37% (5.68%)	1.92% (2.61%)	1.86% (1.94%)	1.28% (1.23%)
2006	-0.95% (3.48%)	-1.11% (1.80%)	-0.61% (1.20%)	-0.39% (1.34%)
2007	1.39% (4.71%)	1.35% (2.14%)	1.26% (1.23%)	2.02% (1.83%)
2008	3.11% (8.84%)	1.08% (8.40%)	-0.60% (6.76%)	-2.65% (4.70%)
2009	-8.97% (6.11%)	-6.39% (4.72%)	-4.48% (4.53%)	-3.41% (3.86%)
2010	-3.31% (10.90%)	-4.52% (7.99%)	-3.09% (5.24%)	-2.24% (2.79%)
2011	3.72% (14.48%)	4.63% (7.15%)	2.71% (4.37%)	1.30% (3.92%)
2012	-2.58% (6.39%)	-1.64% (4.45%)	-0.11% (4.65%)	0.46% (2.63%)
2013	2.45% (10.66%)	1.05% (6.78%)	-0.45% (3.45%)	-0.73% (2.40%)
2014	-1.04% (3.64%)	-0.34% (1.94%)	0.18% (2.10%)	0.72% (1.40%)
2015	1.13% (3.51%)	1.21% (2.39%)	0.47% (1.87%)	1.41% (2.09%)
2016	9.60% (11.49%)	11.29% (8.55%)	12.46% (4.50%)	11.69% (2.45%)
2017	4.52% (7.69%)	2.49% (4.82%)	1.68% (2.96%)	1.24% (2.05%)
2018	0.77% (2.53%)	0.63% (0.92%)	0.33% (0.74%)	0.61% (0.90%)
2019	0.16% (3.85%)	-0.16% (2.49%)	0.88% (1.63%)	1.08% (1.75%)
2020	4.02% (9.15%)	5.31% (3.28%)	4.85% (1.83%)	4.80% (1.59%)
2021	4.54% (3.51%)	2.56% (3.20%)	1.97% (2.42%)	1.83% (1.91%)

8.2. List of abbreviations

8.3. Overview: Fama French three factor model decile overview

	P10(bottom)	P9	P8	P7	P6	P5	P4	P3	P2	P1(top)	Long-Short
const	0.0078	-0.0005	0.0070	0.0062	0.0059***	0.0097	0.0232*	0.0021	0.0233	0.0294***	0.0197***
	(0.0052)	(0.0032)	(0.0060)	(0.0044)	(0.0022)	(0.0071)	(0.0129)	(0.0021)	(0.0176)	(0.0061)	(0.0074)
Mkt-RF	0.8040***	0.4961***	0.1662	0.2526**	0.3030***	0.4744***	0.2118	0.3684***	0.3424	0.4528***	-0.3506**
	(0.1185)	(0.0731)	(0.1386)	(0.1001)	(0.0514)	(0.1620)	(0.2958)	(0.0482)	(0.4037)	(0.1395)	(0.1695)
SMB	0.3841**	0.2879***	0.2438	0.0953	0.2005***	0.1482	-0.0426	0.0463	0.7368	0.2087	-0.1734
	(0.1693)	(0.1044)	(0.1980)	(0.1430)	(0.0734)	(0.2314)	(0.4226)	(0.0688)	(0.5767)	(0.1993)	(0.2422)
HML	0.2324	0.3980***	0.2070	0.0801	0.0728	0.0813	0.0027	0.1470**	0.2818	-0.1031	-0.3372
	(0.1598)	(0.0986)	(0.1868)	(0.1350)	(0.0693)	(0.2183)	(0.3988)	(0.0649)	(0.5443)	(0.1881)	(0.2285)
R-squared	0.1369	0.1588	0.0110	0.0203	0.1190	0.0262	0.0014	0.1471	0.0077	0.0381	0.0178
R-squared Adj.	0.1301	0.1522	0.0033	0.0126	0.1120	0.0186	-0.0065	0.1404	-0.0001	0.0305	0.0101

Standard errors in parentheses.
* p<.1, ** p<.05, ***p<.01

8.4. Overview: Carhart four factor model decile overview

	P10(bottom)	P9	P8	P7	P6	P5	P4	P3	P2	P1(top)	Long-Short
const	0.0109**	0.0016	0.0075	0.0063	0.0063***	0.0100	0.0223*	0.0016	0.0263	0.0294***	0.0166**
	(0.0051)	(0.0032)	(0.0061)	(0.0044)	(0.0023)	(0.0072)	(0.0131)	(0.0021)	(0.0178)	(0.0062)	(0.0074)
Mkt-RF	0.6576***	0.3981***	0.1391	0.2450**	0.2821***	0.4599***	0.2553	0.3926***	0.2000	0.4539***	-0.2043
	(0.1230)	(0.0756)	(0.1463)	(0.1057)	(0.0542)	(0.1710)	(0.3124)	(0.0507)	(0.4258)	(0.1474)	(0.1775)
SMB	0.4005**	0.2988***	0.2468	0.0961	0.2028***	0.1498	-0.0474	0.0436	0.7527	0.2086	-0.1897
	(0.1666)	(0.1024)	(0.1982)	(0.1433)	(0.0734)	(0.2317)	(0.4232)	(0.0687)	(0.5768)	(0.1996)	(0.2405)
HML	0.0903	0.3029***	0.1807	0.0727	0.0525	0.0673	0.0450	0.1705**	0.1435	-0.1020	-0.1953
	(0.1617)	(0.0994)	(0.1923)	(0.1390)	(0.0712)	(0.2249)	(0.4107)	(0.0667)	(0.5598)	(0.1937)	(0.2334)
MOM	-0.4224***	-0.2828***	-0.0782	-0.0219	-0.0603	-0.0419	0.1256	0.0698	-0.4112	0.0032	0.4221***
	(0.1129)	(0.0694)	(0.1343)	(0.0971)	(0.0497)	(0.1570)	(0.2868)	(0.0466)	(0.3909)	(0.1353)	(0.1629)
R-squared	0.1675	0.1940	0.0119	0.0204	0.1223	0.0264	0.0019	0.1521	0.0106	0.0381	0.0348
R-squared Adj.	0.1588	0.1855	0.0015	0.0102	0.1131	0.0162	-0.0086	0.1432	0.0002	0.0280	0.0247

Standard errors in parentheses.
* p<.1, ** p<.05, ***p<.01

8.5. Fama French three factor results within periods

Period 1 – Fama French Results

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      Excess_Long-Short   R-squared:                       0.012
Model:                            OLS   Adj. R-squared:                 -0.013
Method:                 Least Squares   F-statistic:                    0.4869
Date:                Sat, 06 May 2023   Prob (F-statistic):              0.692
Time:                        11:21:35   Log-Likelihood:                 73.076
No. Observations:                 120   AIC:                            -138.2
Df Residuals:                     116   BIC:                            -127.0
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0283      0.013      2.142      0.034       0.002       0.054
Mkt-RF        -0.3338      0.357     -0.936      0.351      -1.040       0.373
SMB            0.0509      0.355      0.143      0.886      -0.653       0.754
HML           -0.4043      0.484     -0.836      0.405      -1.362       0.554
==============================================================================
Omnibus:                       17.629   Durbin-Watson:                   2.073
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               27.821
Skew:                           0.695   Prob(JB):                     9.09e-07
Kurtosis:                       4.906   Cond. No.                         46.6
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Period 2 – Fama French Results

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      Excess_Long-Short   R-squared:                       0.082
Model:                            OLS   Adj. R-squared:                  0.058
Method:                 Least Squares   F-statistic:                     3.454
Date:                Sat, 06 May 2023   Prob (F-statistic):             0.0189
Time:                        11:21:35   Log-Likelihood:                 76.185
No. Observations:                 120   AIC:                            -144.4
Df Residuals:                     116   BIC:                            -133.2
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0095      0.012      0.779      0.438      -0.015       0.034
Mkt-RF        -0.6333      0.262     -2.419      0.017      -1.152      -0.115
SMB           -0.4509      0.464     -0.971      0.334      -1.371       0.469
HML           -0.3394      0.389     -0.872      0.385      -1.110       0.431
==============================================================================
Omnibus:                       17.135   Durbin-Watson:                   2.350
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               74.460
Skew:                          -0.088   Prob(JB):                     6.78e-17
Kurtosis:                       6.855   Cond. No.                         39.9
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Period 3 – Fama French Results

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      Excess_Long-Short   R-squared:                       0.017
Model:                            OLS   Adj. R-squared:                 -0.008
Method:                 Least Squares   F-statistic:                    0.6811
Date:                Sat, 06 May 2023   Prob (F-statistic):              0.565
Time:                        11:21:35   Log-Likelihood:                 49.463
No. Observations:                 120   AIC:                            -90.93
Df Residuals:                     116   BIC:                            -79.78
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0198      0.016      1.245      0.216      -0.012       0.051
Mkt-RF        -0.0382      0.399     -0.096      0.924      -0.828       0.752
SMB           -0.8842      0.691     -1.280      0.203      -2.252       0.484
HML            0.0643      0.579      0.111      0.912      -1.083       1.212
==============================================================================
Omnibus:                       59.356   Durbin-Watson:                   2.067
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              277.995
Skew:                           1.648   Prob(JB):                     4.31e-61
Kurtosis:                       9.689   Cond. No.                         48.2
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

8.6 Carhart Four factor within periods

Period 1 – Carhart Results

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      Excess_Long-Short   R-squared:                       0.012
Model:                            OLS   Adj. R-squared:                 -0.022
Method:                 Least Squares   F-statistic:                    0.3632
Date:                Sat, 06 May 2023   Prob (F-statistic):              0.834
Time:                        11:35:45   Log-Likelihood:                 73.078
No. Observations:                 120   AIC:                            -136.2
Df Residuals:                     115   BIC:                            -122.2
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0286      0.014      2.043      0.043       0.001       0.056
Mkt-RF        -0.3332      0.358     -0.930      0.354      -1.043       0.376
SMB            0.0558      0.364      0.153      0.878      -0.665       0.776
HML           -0.4140      0.506     -0.819      0.415      -1.416       0.588
MOM           -0.0242      0.350     -0.069      0.945      -0.717       0.669
==============================================================================
Omnibus:                       17.444   Durbin-Watson:                   2.071
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               27.380
Skew:                           0.690   Prob(JB):                     1.13e-06
Kurtosis:                       4.890   Cond. No.                         47.4
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Period 2 – Carhart Results

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      Excess_Long-Short   R-squared:                       0.125
Model:                            OLS   Adj. R-squared:                  0.094
Method:                 Least Squares   F-statistic:                     4.093
Date:                Sat, 06 May 2023   Prob (F-statistic):            0.00388
Time:                        11:35:45   Log-Likelihood:                 79.037
No. Observations:                 120   AIC:                            -148.1
Df Residuals:                     115   BIC:                            -134.1
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0091      0.012      0.763      0.447      -0.015       0.033
Mkt-RF        -0.2812      0.297     -0.948      0.345      -0.869       0.307
SMB           -0.4161      0.456     -0.913      0.363      -1.319       0.487
HML           -0.4100      0.383     -1.071      0.286      -1.168       0.348
MOM            0.5183      0.219      2.366      0.020       0.084       0.952
==============================================================================
Omnibus:                       21.305   Durbin-Watson:                   2.368
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              109.080
Skew:                          -0.265   Prob(JB):                     2.06e-24
Kurtosis:                       7.641   Cond. No.                         40.0
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Period 3 – Carhart Results

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      Excess_Long-Short   R-squared:                       0.018
Model:                            OLS   Adj. R-squared:                 -0.016
Method:                 Least Squares   F-statistic:                    0.5336
Date:                Sat, 06 May 2023   Prob (F-statistic):              0.711
Time:                        11:35:45   Log-Likelihood:                 49.519
No. Observations:                 120   AIC:                            -89.04
Df Residuals:                     115   BIC:                            -75.10
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0194      0.016      1.212      0.228      -0.012       0.051
Mkt-RF         0.0010      0.418      0.002      0.998      -0.827       0.829
SMB           -0.8543      0.699     -1.222      0.224      -2.240       0.531
HML            0.1625      0.655      0.248      0.804      -1.135       1.460
MOM            0.1750      0.536      0.326      0.745      -0.887       1.237
==============================================================================
Omnibus:                       59.531   Durbin-Watson:                   2.060
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              279.684
Skew:                           1.653   Prob(JB):                     1.85e-61
Kurtosis:                       9.709   Cond. No.                         49.2
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

8.7 **Rolling 12-Month Volatility of Long Short Returns, 1990-2022**