Academic Year

2023 - 2024

Perceived market dependence and its effect on stock returns

An empirical analysis of European markets

Luna Geens

Master's thesis to obtain the degree of

Digital Business Engineering

Promotors

Prof. dr. Jan Annaert

University of Antwerp
Faculty of Business and Economics

Abstract

This thesis compares the perceived dependence of stock and market returns, as measured by the frequency of comovement following Ungeheuer and Weber (2020), with the traditional interpretation of market dependency measured by Sharpe's beta (1964). Using a dataset of European stock returns from the STOXX EUR 600 index from January 2002 to February 2024, the study categorizes stocks into portfolios based on their comovement after controlling for beta. The findings reveal that portfolios with higher frequencies of comovement exhibit higher average monthly excess returns. The high-low comovement strategy, which involves buying stocks with high frequency of comovement and selling stocks with low frequency of comovement, also yields significant excess returns. Specifically, this strategy results in an a yearly return premium of 6.77% under the Capital Asset Pricing Model (Sharpe, 1964), 7.47% under the three-factor model (Fama & French, 1993), 5,41% under the four-factor model (Carhart, 1997), and 10.59% under the five-factor model (Fama & French, 2015). Robustness tests using alternative factors and indexes, weighted portfolios, and Fama-MacBeth regressions show similar results, although the comovement return premium varies substantially across regions and time periods. Contrary to the frequency of comovement, this study finds limited empirical evidence for a return premium associated with market risk as measured by historical correlation.

Executive Summary

Markowitz's Modern Portfolio Theory (1952) highlights the importance diversification to mitigate unsystematic risk. The Capital Asset Pricing Model (Sharpe, 1964) extends this theory into an equilibrium model of asset prices. The CAPM introduces the security market line, which demonstrates that the expected return on a stock $E(R_i)$ is directly proportional to its systematic risk alone. The CAPM formula is expressed as $E(R_i) = R_f + \beta_i * (E(R_m) - R_f)$, where R_f is the risk-free rate, $E(R_m)$ is the expected market return, and β_i measures a stock's sensitivity to market movements. This model posits that higher beta stocks, which react more strongly to market changes, should offer higher expected returns as compensation for higher market risk. In the past and common practice, empirical asset pricing researchers have used correlation between historical stock and market returns as a proxy for beta.

Despite its popularity, empirical research over the years has challenged the notion of beta in the Capital Asset Pricing Model (Fama & French, 2003). Several explanations have been given as to why beta is not priced. Firstly, empirical research has challenged the notion that beta is the sole determinant of expected returns, leading to the development of multifactor models. Fama-French extended the CAPM by incorporating size and value factors (1993), and later, profitability and investment factors (2015). Carhart (1997) proposed a Four-Factor Model by adding momentum. Additionally, other researchers have proposed various factors to address anomalies in CAPM's predictions (Asness et al., 2017; Frazzini & Pedersen, 2014; Kelly & Jiang, 2014; Keloharju et al., 2016; Koijen et al., 2016; Pastor & Stambaugh, 2001; Sadka, 2003). Secondly, the CAPM’s assumptions have been critiqued for being overly simplistic and unrealistic (Blitz et al., 2013). The model assumes the existence of the risk-free asset, which does not actually exist. Even if it did, the risk-free rate fluctuates over time (DeJong & Collins, 1985) and differs between borrowing and lending (Black, 1972; Friend & Blume, 1970). The true market portfolio of the CAPM, which should encompass all assets, is unobservable (Roll, 1977) and thus stock indexes are used as proxies. The CAPM also assumes homogeneous expectations regarding returns and market dependencies, whereas investors actually have diverse information and varying beliefs (Aghion et al., 2003) and consider factors beyond mean and variance. Sharpe's CAPM focuses on investments over a single period, whereas Merton (1973) extends the model to a multi-period framework. The CAPM also assumes a frictionless market without taxes, transaction costs, or restrictions on short selling, which various researchers contest (Constantinides, 1986; Pastor & Stambaugh, 2001; Reilly & Brown, 2011). Thirdly, the CAPM faces significant empirical testing difficulties. Beta measurements, traditionally calculated through the correlation of historical returns, are unstable over time (Blume, 1971, 1975; Ferson & Harvey, 1991; Jagannathan & Wang, 1996). The notion of correlation neglect suggests that investors might not fully consider the dependency between a stock’s return and the market return, leading to misestimations of market risk (Enke & Zimmermann, 2013; Eyster & Weizsacker, 2016). However, recent studies show that people do not neglect dependence in pricing assets (Laudenbach et al., 2019) but perceive dependence differently than historical correlation suggest (Ungeheuer & Weber, 2020). Bossaerts and Plott (2004) find that the CAPM’s pricing implications hold when market participants' beliefs about beta are unbiased.

Ungeheuer and Weber (2020) propose using the frequency of comovement of stocks instead of correlation as a measure of perceived dependence. While correlation measures the magnitude of two returns moving together, the frequency of comovement focuses on the direction in which two returns move together (i.e., having the same sign). This approach, akin to using a simple counting heuristic, underweights extreme returns compared to correlation. In their studies, participants correctly understood the changes in dependence in moderate returns but failed to grasp the dependence in extreme returns. When asked about overall dependence, participants aligned their beliefs with those about moderate returns, even if they understood changes in extreme returns. Thus, Ungeheuer and Weber (2020) proposed the frequency of comovement as a more accurate indicator of perceived dependence, suggesting that investors use a simple “counting heuristic” to assess dependence rather than understanding and accurately interpreting complex statistical measures like correlation. The findings of Ungeheuer and Weber (2020) have implications for asset pricing. They suggest that stocks with a higher frequency of comovement with market returns are perceived to have higher market risk, resulting in a higher return premium according to the CAPM. Their analysis of U.S. common shares from the NYSE, AMEX, and NASDAQ from 1963 to 2015 supports this hypothesis. By applying a high-minus-low comove strategy (i.e., buying the portfolio with the highest comovement frequency and selling the portfolio with the lowest comovement frequency), Ungeheuer and Weber (2020) find a return premium of 4.28% per year after controlling for beta. The return premium remains statistically significant, ranging between 3.49% and 6.16%, when controlling for various other factors.

This paper aims to test the following hypothesis: (H1) stocks with a higher frequency of comovement between their returns and market returns result in a return premium compared to stocks with lower frequency of comovement. To test H1, the expected returns of portfolios composed of stocks with similar levels of comovement frequency are analysed. The prediction of these portfolios' expected returns is conducted using the CAPM and extended factor models, with monthly return predictions spanning from January 2002 to February 2024. Data is retrieved from DataStream software in euros. The monthly market return is represented by the STOXX Europe 600 index. Portfolios are formed from stocks that are constituents of this index during each respective month. The individual stock returns are calculated based on their performance during the month, while the beta and frequency of comovement are determined using returns from the 52 weeks preceding each month. Stocks are sorted into quintiles based on their beta values, and then further subdivided into quintiles by their frequency of comovement within each beta quintile. This results in five distinct portfolios each month that are in the same comovement quintile across beta quintiles, each characterized by a strong exposure to comovement while maintaining relatively constant beta across portfolios. Due to the presence of autocorrelation, standard Ordinary Least Squares estimators are unsuitable. Newey-West estimators (1986), adjusted for a single lag, are employed to correct for time-dependency in returns.

The main results in this paper support this hypothesis. Portfolios with high comovement (Rank 5) generally exhibit higher volatility and peaks compared to low comovement portfolios (Rank 1), though the differences are not statistically significant. Patton and Timmerman monotonicity tests (2010) suggest an increasing relationship in return across all comove ranks. Regression analysis using Newey-West estimators (1986) shows that the monthly difference of 0.50% between the extreme ranks has a high p-value of 0.1441, indicating no significant difference in return premium. Regression analysis using the Carhart (1997) four-factor model shows that portfolios within the lowest comovement rank have a monthly alpha of 0.16%, while those in the highest comove rank achieve a monthly excess return of 0.61%. The alpha for a high-low comovement strategy is thus calculated as an annual return of 5.41%, statistically significant at the 10% level. This suggests that, after adjusting for Carhart's four factors (1997), the high-low strategy based on comovement yields significant excess returns. A high-low comove strategy was also employed for different factor models, including CAPM (Sharpe, 1964), the three-factor model (Fama & French, 1993), and the five-factor model (Fama & French, 2015). The results show a return premium between 6.77% and 10.59% per year, all statistically significant at the 1% level. Additional factors like the quality-minus-junk factor (Asness et al., 2017), the betting-against-beta factor (Frazzini & Pedersen, 2014), the carry factor (Koijen et al., 2016), and seasonality effects (Keloharju et al., 2016) were also considered. Despite these extensions, the comovement return premium remains significant. A sample split into January 2002 – December 2012 and January 2013 – February 2024 shows a stronger return premium in the earlier period. The four-factor model (Carhart,

1997) for the latter subsample (2013-2024) yields results that are low and statistically insignificant, while the five-factor model (Fama & French, 2015) demonstrates significance at the 1% level across both subsamples with a lower return in the latter period. This contradicts the work of Ungeheuer and Weber (2020), in which results over their 1963-1988 and 1989-2015 subsamples suggest an increasing trend of comovement premium in time.

Robustness tests include alternative factor measures, alternative indexes, value-weighted portfolios, and Fama and MacBeth regressions (1973). These tests consistently show that the comovement premium is robust across different methodologies and datasets. Adjusting for more accurate or comprehensive factor measures results in similar or slightly higher comovement premiums. Using national equity indexes shows varying comovement return premiums across different regions, though results are not significant due to limited data. Both equal-weighted and value-weighted portfolios show consistent comovement premiums. Fama and MacBeth regressions (1973) show significant comovement premiums, with beta consistently exhibiting a negative return premium. In those Fama and MacBeth regressions (1973), the comove return premium remains around 7% and statistically significant after controlling for other measures of dependency and volatility, such as asymmetric systematic risk, idiosyncratic risk, and liquidity risk. Other benchmarks, such as different momentums, operating profitability and investment, and fixed effects for industries, stock exchanges, and comove with a skipped month show varying results. Other ways of calculating comove show small and mostly insignificant comove return premiums. When excluding stocks on the London Exchange, small-cap stocks, or stocks with an end-of-the-month price below $5, a similar yearly return premium of 7.07% is found. Splitting up the sample reveals a strong return premium in the earlier period (17.75%) and a negative but insignificant yearly return premium for the latter period (-3.44%).

When compared to Ungeheuer and Weber (2020), the European market exhibits a lower comovement frequency and slightly higher beta values compared to the U.S. market, with average (median) comovement at 51.65% (51.92%) and beta at 0.9915 (0.9635). Notably, the correlation between comovement and beta is negligible (0.01) in this paper, suggesting that comovement with the market does not align closely with systematic risk as measured by beta. Furthermore, high-low investment strategies based on comovement frequency generated positive cumulative returns, whereas similar strategies based on beta produced negative cumulative returns when adjusted for the Carhart four factors (1997). Contrary to the Capital Asset Pricing Model (CAPM) predictions, beta exhibited a significant negative coefficient in nearly all Fama and Macbeth regressions. These findings underscore the importance of considering comovement frequency as a distinct factor in portfolio construction and risk assessment, beyond traditional beta measurements.

List of Figures

Figure 1 - Average Beta and Frequency of Comovement for Portfolios with Comove rank 1 and 5 over Time....19

Figure 2 - Cumulative Average Return Excess for Comove Rank 1 and 5 over Time. 20

Figure 3 – Cumulative Carhart (1997) Alpha of High-Low portfolio over time: double-sorting on beta first and comove second (Comove strategy) versus double-sorting on comove first and beta second (Beta strategy)....23

Figure 4 - (Partial) Autocorrelation Function for Portfolio's with Comove Rank 1. 43

Figure 5 - Average Return Excess for Comove Rank 1 and 5 over Time. 44

Figure 6 - Average Beta and Frequency of Comovement for Portfolios with Beta rank 1 and 5 over Time. 44

Figure 7 - Estimated Alpha per Factor Model, Across Different Time Periods. 45

Figure 8 - Cumulative Carhart (1997) Alpha of High-Low portfolio over time for various national indexes: double-sorting on beta first and comove second (Comove strategy) versus double-sorting on comove first and beta second (Beta strategy). 46

Figure 9 - Correlations between variables of Fama and MacBeth regressions. 47

Figure 10 - Normalized Monthly Averages Over Time of Comove, Beta, and Measures of Upside and Downside Risk. 48

Figure 11 - Normalized Monthly Averages Over Time of Comove and Measures of Idiosyncratic Risk. 48

Figure 12 - Comove Return Premium Over Time, after controlling for a Carhart's (1997) four factors with Fama and MacBeth regressions. 49

Figure 13 - Google Searches for the search term "Risk" worldwide in the category exchanges and financial support (Google Searches for the Search Term 'Risk', 2024). 49

List of Tables

Table 1 - Set-up of the third experiment described in "The Perception of Dependence, Investment Decisions and Stock Prices" by M. Ungeheuer and M. Weber. 15

Table 2 - Illustration of Time Intervals used in the Definition of Variables for Individual Stocks. An example is given for the month January. 17

Table 3 - Summary of Main Results 50

Table 4 - Summary of Robustness Results with Alternative Factor Measures 51

Table 5 - Summary of Robustness Results with Alternative Index 51

Table 6 - Summary of Robustness Results with Alternative Portfolio Aggregation 52

Table 7 - Univariate Distributions of the Main Variables used in Robustness Tests with Fama and MacBeth Regressions. 53

Table 8 - Summary of Robustness Results with Fama and MacBeth Regressions and Other Measurements of Dependence and Volatility. 54

Table 9 - Summary of Robustness Results with Fama and MacBeth Regressions and Other Benchmarks, Fixed Effects and Comove with a Skipped Month. 55

Table 10 -Summary of Robustness Results with Fama and MacBeth Regressions while varying the Comove measure and the sample. 56

Table 11 - Overview of Equity Pricing Factors: Data definitions and sources. 57

Table 12 - Main variables used in Fama and MacBeth Regressions, illustrated for the month January. 61

Table 13 - Other measurements of dependency and volatility used in Fama and MacBeth Regressions, illustrated for the month January. 62

Table 14 - Other benchmarks, fixed effects and adjusted comove with skipped month as used in Fama and MacBeth Regressions, illustrated for the month January. 63

Table 15 - Variables used when varying the comove measure and the sample in the Fama and MacBeth regressions, illustrated for the month January. 64

Table of Contents

Abstract 2
Executive Summary 3
List of Figures 6
List of Tables 7
1 Introduction 10
1.1 Market Risk in the Capital Asset Pricing Model 10
1.2 Contribution to Literature 11
1.3 Contribution to Sustainable Development Goals 11
2 Literature Overview 12
2.1 Introduction to the Capital Asset Pricing Model 12
2.2 Anomalies of the Capital Asset Pricing Model 12
2.2.1 Factor Models 12
2.2.2 Critique on Assumptions 13
2.2.3 Empirical Testing Difficulties 14
2.3 Correlation and Perceived Dependence 15
2.4 Return and Perceived Dependence 16
3 Methodology 17
3.1 Data Collection 17
3.2 Data Sorting 18
3.3 Autocorrelation 19
4 Empirical Results: Frequency of Comovement as an Unexplained Return Premium 20
4.1 Main Results 20
4.1.1 Relationship between Excess Portfolio Return and Comove Rank 20
4.1.2 Carhart's Factor Model Adjustment 21
4.1.3 High-Low Comove Strategy 22
4.1.4 Sample Split 23
4.2 Robustness Tests 24
4.2.1 Alternative Factor Measures 24
4.2.2 Alternative Index 24
4.2.3 Alternative Portfolio Aggregation 25
4.2.4 Controlling with Fama and MacBeth Regressions 25
4.2.4.1 Other Measurements of Dependency and Volatility 26
4.2.4.2 Other Benchmarks, Fixed Effects and Skipped Month 28
4.2.4.3 Varying the Comove Measure and the Sample 29

5 Conclusion 31
5.1 Key Findings 31
5.2 Key Insights 33
5.3 Suggestions for Future Research 34
6 Bibliography 36
7 Additional Figures 43
8 Additional Tables 50
9 Appendix 57
9.1 Appendix A: Overview of Variables in Equity Pricing Factor Models 57
9.2 Appendix B: Overview of Variables in Fama & MacBeth Regressions 61
9.3 Appendix C: Use of Technologies 65
9.3.1 Data Collection Technologies 65
9.3.2 Data Processing Technologies 65
9.3.3 AI-Related Technologies 66
10 Declaration On Word of Honour 67

1 Introduction

1.1 Market Risk in the Capital Asset Pricing Model

Since its introduction in the 1960s, the Capital Asset Pricing Model (CAPM) (Sharpe, 1964) has been widely adopted in the economic literature to understand the relationship between risk and expected return of a stock in capital markets. The CAPM states that the expected return on an investment $E(R_i)$ is directly proportional to its systematic risk:

$$E(R_i) = R_f + \beta_i \left(E(R_m) - R_f\right)$$

Assuming that unsystematic risk can be eliminated through diversification (Markowitz, 1952), the CAPM focuses solely on systematic risk. As an asset reacts more strongly to market changes, it is expected to offer higher returns as a reward for taking on higher market risk. Sharpe (1964) introduced the concept of beta (β) as the sensitivity of a stock's return to market movements. In the past and common practice, empirical asset pricing researchers have used correlation between historical stock and market returns as a proxy for beta. Note that this implies an extra assumption of historical returns being able to predict future ones; one that is not included in Sharpe's original work.

As delineated in Section 2, various explanations have been proposed to explain why empirical studies indicate that beta has not been effectively incorporated into actual stock market prices (Fama & French, 2003). One hypothesis, called 'correlation neglect,' suggests that investors may not fully account for the dependence between the returns of individual stocks and the broader market, thereby misestimating the market risk associated with specific stocks (Enke & Zimmermann, 2013; Eyster & Weizsacker, 2016). Conversely, recent scholarship challenges this view by suggesting that investors do consider dependencies in asset pricing (Laudenbach et al., 2019), albeit perceiving these dependencies differently than historical correlations suggest. For instance, Ungeheuer and Weber (2020) argue against the presence of correlation neglect when information is presented using a realistically sampled format. Instead of traditional correlation metrics, they suggest that the frequency of comovement between stock returns and market returns serves as a more relevant measure of perceived dependence.

Integrating the Capital Asset Pricing Model with this proposal, stocks with higher frequency of comovement between their returns and market returns would be seen as stocks with a higher market risk, resulting in a higher return premium relative to stocks with a lower frequency of comovement. Ungeheuer and Weber (2020) analysed U.S. common shares from the NYSE, AMEX, and NASDAQ to confirm this hypothesis. When applying a high-minus-low comove strategy, Ungeheuer and Weber (2020) find a return premium of 4.28% per year after controlling for beta. This research paper seeks to validate the same hypothesis within the European market context. The study also seeks to investigate whether the frequency of comovement serves as a more effective metric than correlation for predicting returns within the Capital Asset Pricing Model (CAPM).

1.2 Contribution to Literature

This thesis contributes to the literature on empirical asset pricing by challenging traditional metrics used to assess market dependency and proposing an alternative approach. Traditional metrics, such as Sharpe's beta (1964), have long been a cornerstone of asset pricing models but have faced criticism for their lack of empirical support (Fama & French, 2003). One explanation for this shortcoming is the hypothesis of 'correlation neglect,' which suggests that investors might not fully account for the dependence between individual stock returns and the broader market, leading to misestimations of market risk (Enke & Zimmermann, 2013; Eyster & Weizsacker, 2016). This thesis, along with recent scholarship (Ungeheuer & Weber, 2020), challenges this view by suggesting that investors do consider dependencies in asset pricing, though they perceive these dependencies differently than historical correlations suggest. By introducing an alternative metric, this analysis enriches the academic discourse on market dependency and enhances the predictive accuracy of asset pricing models in capturing return premia that beta may overlook. Moreover, the thesis contributes to behavioral finance literature by challenging the notion of mean-variance investors as assumed in the Capital Asset Pricing Model (Sharpe, 1964).

Furthermore, the empirical findings of this study extend the work of Ungeheuer and Weber (2020), who proposed the frequency of comovement as a more accurate indicator of perceived dependence in North American markets. This approach, akin to using a simple counting heuristic, underweights extreme returns compared to correlation. Supporting this, neuroscience suggests that humans struggle to detect and adapt to extreme outcomes (Bossaerts & Plott, 2004). This thesis provides robust evidence supporting Ungeheuer and Weber's hypothesis within the context of the European stock market. This empirical validation in a different market setting corroborates previous findings and enhances its applicability in global asset pricing models.

In addition to its primary focus, this thesis contributes to several areas of existing research. One notable contribution is the exploration of the comovement premium across different time periods. The study's analysis of two distinct periods, January 2002 to December 2012 and January 2013 to February 2024, reveals a noticeable decline of the comove return premium in the latter period. This decline partly contradicts findings of Ungeheuer and Weber (2020) and highlights the dynamic nature of the comovement premium over time. This observation does align with other studies showing that beta, another measure of market dependency, also varies over time (Blume, 1971, 1975; Ferson & Harvey, 1991; Jagannathan & Wang, 1996). Additionally, the thesis examines the impact of various risk factors on the comovement premium, including upside and downside risk, idiosyncratic risk, and liquidity risk. This risk-adjusted analysis not only confirms the robustness of the comovement premium but also identifies its interactions with other well-known risk factors, contributing to the broader asset pricing literature and offering practical insights for portfolio management.

1.3 Contribution to Sustainable Development Goals

The contribution to the Sustainable Development Goals (United Nations, 2015) is modest but not negligible. Enhanced understanding of human behavior in stock markets could benefit goals such as SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation, and Infrastructure). Such knowledge could lead to greater market stability and more accurate risk assessments for sustainable portfolios. Furthermore, leveraging the Comove return premium could help generate capital to finance projects aligned with the Sustainable Development Goals.

2 Literature Overview

2.1 Introduction to the Capital Asset Pricing Model

In Modern Portfolio Theory, Markowitz (1952) introduced the concept of diversification. He showed that unsystematic risks, specific to individual stocks, can be mitigated by holding a diverse set of stocks. Markowitz also developed the efficient frontier, which represents portfolios that offer the highest expected return for a given level of risk. This was further quantified through mean-variance analysis, which evaluates the trade-off between risk (variance) and return (mean).

Sharpe (1964) developed the Capital Asset Pricing Model (CAPM), which extends Markowitz's Modern Portfolio Theory (1952) to an equilibrium model of asset prices. The CAPM introduces the security market line, which shows that the expected return on a stock $E(R_i)$ is directly proportional to its systematic risk:

$$E(R_i) = R_f + \beta_i \left(E(R_m) - R_f\right)$$

Assuming that unsystematic risk can be eliminated through diversification (Markowitz, 1952), the CAPM focuses solely on systematic risk. As an asset reacts more strongly to market changes, it is expected to offer higher returns as a reward for taking on higher market risk. Sharpe (1964) introduced the concept of beta (β) to measure a stock's sensitivity to market movements, indicating the degree to which the return of an asset reacts to market changes.

Around the same time as William Sharpe (1964), John Lintner (1965) independently developed a version of the CAPM. Both models describe the expected return of a security based on its systematic risk, as measured by beta. Since its introduction in the 1960s, the Capital Asset Pricing Model (CAPM) (Sharpe, 1964) has been widely adopted in the economic literature to understand the relationship between risk and expected return of a stock in capital markets.

2.2 Anomalies of the Capital Asset Pricing Model

Despite its popularity, empirical research over the years has challenged the notion of beta in the Capital Asset Pricing Model (Fama & French, 2003). Several explanations have been given as to why beta is not priced.

2.2.1 Factor Models

Firstly, and perhaps the most popular one, is the adoption of **additional variables** beside market risk that could influence the expected return. The Fama-French Three-Factor model (Fama & French, 1993) extends the CAPM (Sharpe, 1964) with two additional factors: size and value. According to the model, small-cap and value stocks imply higher risk and therefore higher expected return. Over twenty years after the introduction of their three-factor model, Fama and French added profitability (robust versus weak) and investment (conservative versus aggressive) as factors in their Five-Factor Model (Fama & French, 2015).

Building on the three-factor model, Carhart (1997) added momentum as a fourth factor: he suggested that stocks that have performed well in the past (so-called "winners") will continue to do so. The Q-Factor model (Hou et al., 2015) incorporates market risk, size, profitability, and investment as well, albeit under different measurements, but not Carhart's momentum factor or Fama and French's value factor.

Other researchers have proposed different factors: examples are the betting-against-beta factor (Frazzini & Pedersen, 2014), the tail risk factor (Kelly & Jiang, 2014), the liquidity factor (Pastor & Stambaugh, 2001), the systematic liquidity factors (Sadka, 2003), the undervalued-minus-overvalued factor (Hirshleifer & Jiang, 2010), the quality-minus-junk factor (Asness et al., 2017), the mispricing factors (Stambaugh & Yuan, 2016), the carry factor (Koijen et al., 2016) and the seasonality factor (Keloharju et al., 2016).

More general, the Arbitrage Pricing Theory (Ross, 1976) is a multi-factor model that suggests that assets returns can be modeled as a linear function of numerous factor variables, but not specify particular risk factors. Additionally, macro factor and global factor models extend the concept of factor investing beyond specific markets or asset classes. For example, Chen et al. (1986) find that unexpected changes in inflation, industrial production, risk premiums, and the shape of the yield curve are all priced sources of risk.

To conclude, many factor models have been proposed to address some of CAPM's empirical anomalies and provide a more nuanced understanding of the forces driving asset returns. However, even with additional variables, there is conflicting empirical evidence for these so-called "factor models" (Celik, 2012).

2.2.2 Critique on Assumptions

Secondly, Blitz et al. (2013) critique the CAPM for its reliance on **assumptions that are both unrealistic and overly simplistic**.

Among the assumptions under scrutiny, the CAPM (Sharpe, 1964) supposes that all investors hold a combination of the market portfolio, containing all available assets and the risk-free asset. Consequently, the CAPM suggests the existence of a risk-free rate. In reality, there is no truly risk-free asset and even if such risk-free rate can be approximated, the rate would change over time (DeJong & Collins, 1985). Friend and Blume (1970) highlight the discrepancies between borrowing and lending risk-free rates. Black (1972) proposes a model with risk-free lending but not borrowing. Additionally, the true market portfolio is unobservable as it should include all types of assets (e.g., stocks, bonds, real estate, human capital) (Roll, 1977). In practice, proxies like stock indexes are used which do not capture the entire market.

Furthermore, the CAPM's (Sharpe, 1964) underlying efficient market hypothesis posits that investors have homogeneous expectations regarding returns and market sensitivities. Following Markowitz (1952), the CAPM characterizes all market participants as mean-variance investors who makes decisions based solely on the expected returns (mean) and the variance of returns (risk) to maximize their utility. In reality, investors have diverse information and hold varying beliefs (Aghion et al., 2003). Moreover, real-world investors consider aspects beyond just mean and variance. Previously mentioned factor models suggested considering other financial aspects such as liquidity (Pastor &

Stambaugh, 2001; Sadka, 2003) and skewness of returns (Kelly & Jiang, 2014). Behavioral finance fundamentally challenges this notion of a "homo economicus." Several scholars have even tried to incorporate some behavioral insights, such as investment sentiment (Baker & Wurgler, 2006), into a factor model.

Additionally, Sharpe (1964) focuses on investments over a single, upcoming time period. In contrast, Merton (1973) extends the CAPM to a multi-period model. Merton's Intertemporal Capital Asset Pricing Model accounts for the fact that that investors not only seek to maximize their utility based on current consumption and wealth but also hedge against changes in the investment opportunity set over time. For example, a young adult investing for retirement would consider not only the expected return and risk for the upcoming year but also how economic factors, such as interest rates, inflation, and market conditions, might impact their investment opportunities over the next 30 years.

Lastly, the model assumes that investments occur in a market without taxes, transaction costs, or restrictions on short selling. Constantinides (1986) explores the impact of transaction costs on the capital market, challenging the frictionless market assumption of the CAPM. Reilly and Brown (2011) suggest that the rate of return used through the model was before taxes and suggest an alternative formula for the actual returns. Factor models that incorporate liquidity, such as the one proposed by Pastor and Stambaugh (2001), show that there is a priced liquidity risk to assets. This is due to the reality that assets cannot be bought and sold instantly without impacting the asset's price.

2.2.3 Empirical Testing Difficulties

Thirdly, previously mentioned challenges such as the unobservable market portfolio and the theoretical emphasis on returns in one upcoming period underscore the **empirical testing difficulties** faced by the CAPM. Beta measurements are traditionally calculated through the correlation of historical returns. Empirical evidence has shown that beta is unstable over time (Blume, 1971, 1975; Ferson & Harvey, 1991; Jagannathan & Wang, 1996). This variability complicates the prediction of future returns using historical betas.

The notion of correlation neglect suggests that investors might not fully consider the dependency of the stock's return and the market return, and therefore misestimate the market risk of stock (Enke & Zimmermann, 2013; Eyster & Weizsacker, 2016). Such oversight challenges the CAPM's premises that the market portfolio is optimally diversified based on these correlations and might lead to mispriced assets.

In contrast, more recent studies show that people do not neglect dependence in pricing assets, but that they perceive dependence differently than historical correlation. Bossaerts and Plott (2004) find that the CAPM's pricing implications hold when market's participant's beliefs about beta are unbiased. In contrast to CAPM's assumption of homogenous expectation and efficient markets, investors have diverse information and beliefs about beta. Laudenbach et al. (2019) do not find correlation neglect when information is presented in a realistic sample format, and point out that studies who find correlation neglect use return distribution descriptions that might confuse participants.

2.3 Correlation and Perceived Dependence

In particular, Ungeheuer and Weber (2020) propose the frequency of comovement of stocks instead of correlation as a measurement for perceived dependence. Correlation refers to the magnitude in which two returns move together, whereas frequency of comovement refers to the direction in which two returns move together (i.e., having the same sign). This approach, akin to using a simple counting heuristic, underweights extreme returns compared to correlation.

In the studies presented, participants were shown one hundred return pairs from the two stocks per experiment. Participants were instructed to articulate their beliefs about overall dependence, dependence in extreme returns and dependence in moderate returns of the two stocks. Additionally, each participant was tasked to allocate $10.000 between the two investment options. Stock A has an average return of 5% and stock B provided an average return of 4% in all experiments. Investment in stock B could therefore only be justified by its diversification benefits. The CAPM suggests that investors would diversify more in stock B if the correlation between stock A and B's returns is lower, since there are more diversification benefits in that case. Nonetheless, the third experiment had surprising outcomes. The set-up was the following:

Table 1 - Set-up of the third experiment described in "The Perception of Dependence, Investment Decisions and Stock Prices" by M. Ungeheuer and M. Weber.

<table>
<tr><th colspan="5">Set-up of the third experiment</th></tr>
<tr><th></th><th>Dependence in moderate returns</th><th>Dependence in extreme returns</th><th>Frequency of comovement</th><th>Correlation</th></tr>
<tr><td rowspan="3">Treatment 1</td><td>The dependence in moderate returns is positive.</td><td>The dependence in extreme returns is negative.</td><td rowspan="3">90%</td><td rowspan="3">-0.21</td></tr>
<tr><td>In 45 of 100 return pairs, stock A has a return of -5% and stock B has a return of -6%.</td><td>In 5 of 100 return pairs, stock A has a return of -32% and stock B has a return of 41%.</td></tr>
<tr><td>In 45 of 100 return pairs, stock A has a return of 15% and stock B has a return of 14%.</td><td>In 5 of 100 return pairs, stock A has a return of 42% and stock B has a return of -33%.</td></tr>
<tr><td rowspan="3">Treatment 2</td><td>The dependence in moderate returns is negative.</td><td>The dependence in extreme returns is positive.</td><td rowspan="3">10%</td><td rowspan="3">0.21</td></tr>
<tr><td>In 45 of 100 return pairs, stock A has a return of -5% and stock B has a return of 14%.</td><td>In 5 of 100 return pairs, stock A has a return of -32% and stock B has a return of -33%.</td></tr>
<tr><td>In 45 of 100 return pairs, stock A has a return of 15% and stock B has a return of -6%.</td><td>In 5 of 100 return pairs, stock A has a return of 42% and stock B has a return of 41%.</td></tr>
<tr><td>Delta</td><td>Decrease</td><td>Increase</td><td>Decrease</td><td>Increase</td></tr>
</table>

When asked about dependence, participants correctly understood the changes of dependence in moderate returns. Contrarily, most participants either did not understood dependence in extreme dependence or incorrectly projected their beliefs regarding dependence in moderate returns onto extreme returns.

In contrast to actual dependence measured by correlation, participants believed the overall dependence of the stock returns decreased from treatment 1 to 2. Across all experiments, participants beliefs about overall dependence aligned with their beliefs about moderate returns, even if they understood changes in dependence of extreme returns. Therefore, Ungeheuer and Weber (2020) proposed the frequency as comovement as a more accurate indicator of perceived dependence – as if the participants used a simple "counting heuristic" to assess dependence. It seems that investors are simply counting the numbers of times the stocks move together (either up or down) rather than understanding and accurately interpreting more complex statistical measures of dependence like correlation.

Their incorrect beliefs about overall dependence were reflected in the investment decisions of the participants. A mean-variance investor that is maximizing its utility would choose to diversify less in the second treatment due to increased correlation. Nevertheless, because the average participant believed that overall dependence had decreased, they invested an additional 923 euros in stock B in the second treatment.

2.4 Return and Perceived Dependence

The findings of the other experiments in the paper (Ungeheuer & Weber, 2020) confirmed those from the third experiment and posed questions about its real-world implications. Even if many people acted as the participants, Ungeheuer and Weber (2020) were not sure if their investment behavior could drive prices. One might say that an institutionalized investor could exploit this bias, and this would wash out any price effect on the aggregate demand. However, as discussed in Section 2.2, empirical studies have shown that there are unexplained return effects.

Applying the Capital Asset Pricing Model (Sharpe, 1964) with this new metric, stocks with higher frequency of comovement between their returns and market returns would be seen as stocks with a higher market risk, resulting in a higher return premium in comparison to stocks with a lower frequency of comovement. Ungeheuer and Weber (2020) analyzed U.S. common shares from the NYSE, AMEX, and NASDAQ from 1963 to 2015 to test this hypothesis. When applying a high-minus low comove strategy (i.e., buying the portfolio with the highest comovement frequency and selling the portfolio with the lowest comove frequency), Ungeheuer and Weber (2020) find a return premium of 4,28% per year after controlling for beta. When controlling for various other factors, the return premium remained statistically significant and between 3.49% and 6.16%. Splitting up their sample, statistically significant return premiums between 3.61% and 7.82% for different factor models were found in the 1989-2015 period.

The aim of this paper is to evaluate the following hypothesis:

> ***H_1: In the European stock market, stocks with a higher frequency of comovement between their returns and the market returns result in a return premium compared to stocks with lower frequency of comovement.***

3 Methodology

To test H_1, the expected returns of portfolios composed of stocks with a similar level of comovement frequency are analyzed. The prediction of these portfolios' expected returns is conducted using the Capital Asset Pricing Model (CAPM) and extended factor models, with monthly return predictions made from January 2002 to February 2024. The portfolio construction process, detailed below, involves grouping stocks with similar comovement frequency levels. This requires calculating both the correlation (beta) and the frequency of comovement between historical stock returns and market returns. To summarize, collecting individual stock returns and market returns over various time intervals is necessary to calculate monthly returns, beta, and comovement.

3.1 Data Collection

All return indexes are retrieved from DataStream software in euro. The monthly market return is indicated by the STOXX Europe 600 index in that month. Empirical research often utilizes the EUR 600 due to its comprehensive data set. Portfolios are formed from stocks that are constituents of this index during the respective month. As illustrated in Table 2, their individual stock returns are calculated based on their performance during that month. The beta and frequency of comovement for these individual stocks are then determined using their returns from the 52 weeks preceding the given month.

Table 2 - Illustration of Time Intervals used in the Definition of Variables for Individual Stocks. An example is given for the month January.

Time Intervals for Variables of Individual Stocks													
	20XX - 1												**20XX**
	Jan	*Feb*	*March*	*April*	*May*	*June*	*July*	*Aug*	*Sep*	*Oct*	*Nov*	*Dec*	*Jan*
Stocks in the index on …													**Index**
Comove of an Individual Stock	Weekly Returns of Stock and Index												
Beta of an Individual Stock	Daily Returns of Stock and Index												
Return of an Individual Stock													Monthly Difference in Return of Stock

Percentage returns are computed by determining the percentage difference between the return index on the last weekday prior to the specified period and the return index on the last weekday of that period. For example, to determine the **return** of an individual stock in month t, one calculates the percentage difference between the return index on the last weekday of the preceding month t−1 and the last weekday of the month t. Weekends are not included in this calculation as the stock market is closed, and no trading data is available.

The calculation of the **frequency of comovement (shortened as "comove")** for an individual stock in a given month, denoted as t, is derived by examining the weekly percentage returns over the preceding 52 weeks relative to month t for both the individual stock and the market index, specifically the EUR 600. This frequency of comovement is calculated as the percentage of those 52 weeks during which the returns of the individual stock and the EUR 600 index exhibited the same directional movement—either positive or negative.

The computation of the **beta** coefficient for a specific stock in a designated month, labelled as t, is conducted by analyzing the daily percentage returns for both the stock and the market index—specifically the EUR 600—over the 52 weeks preceding month t. Beta is then determined by dividing the covariance between the stock's returns and the market's returns by the variance of the market returns. This process quantifies the relative volatility of the individual stock in comparison to the broader market represented by the EUR 600 index.

Based on the beta and frequency of comovement of individual stocks, stocks included in the index during month t are classified into five distinct portfolios for that same month. The return of each portfolio is calculated as the average return of the stocks contained within it. To test the Capital Asset Pricing Model (CAPM) and its extended factor models, other variables required are held constant across all portfolios for month t. Detailed definitions and sources for the factors are provided in Appendix A.

3.2 Data Sorting

The method used to classify stocks into portfolios follows the same sorting approach as outlined in the study by Ungeheuer and Weber (2020). For each month t, stocks are ranked according to their beta values and segmented into quintiles. Within each beta quintile, the stocks are then ranked based on their frequency of comovement and subdivided into further quintiles. For instance, within each beta quintile, stocks exhibiting the lowest frequency of comovement are assigned a comovement rank of 1, while those with the highest frequency are designated a comovement rank of 5. Stocks across different beta quintiles that share the same comovement rank are grouped into a single portfolio.

This methodology facilitates the organization of stocks into five distinct portfolios each month, each characterized by a strong exposure to Comove while holding Beta relatively constant across portfolios. As illustrated in Figure 1, the average Beta of stocks in portfolios characterized by a low frequency of comovement is closely aligned with that of stocks in portfolios with a high frequency of comovement. Specifically, portfolios with high Comovement register an average Beta (β) of 0.9871, whereas those with low Comovement show an average Beta of 0.9930. The difference in Beta between these extreme portfolios is -0.0059, or -300.89% of Beta's standard deviation (0.0020). In contrast, there is a significant disparity in average Comovement across portfolios: high Comove portfolios have an average Comove of 62.3631, while low Comove portfolios display an average Comove of 42.2978, representing a variation of 20.07, or -3921.26% of Comove's standard deviation (-0.5117). Because Beta is controlled and nearly constant, any differences in returns between portfolios can be more confidently attributed to the differences in Comove rather than to differences in beta.

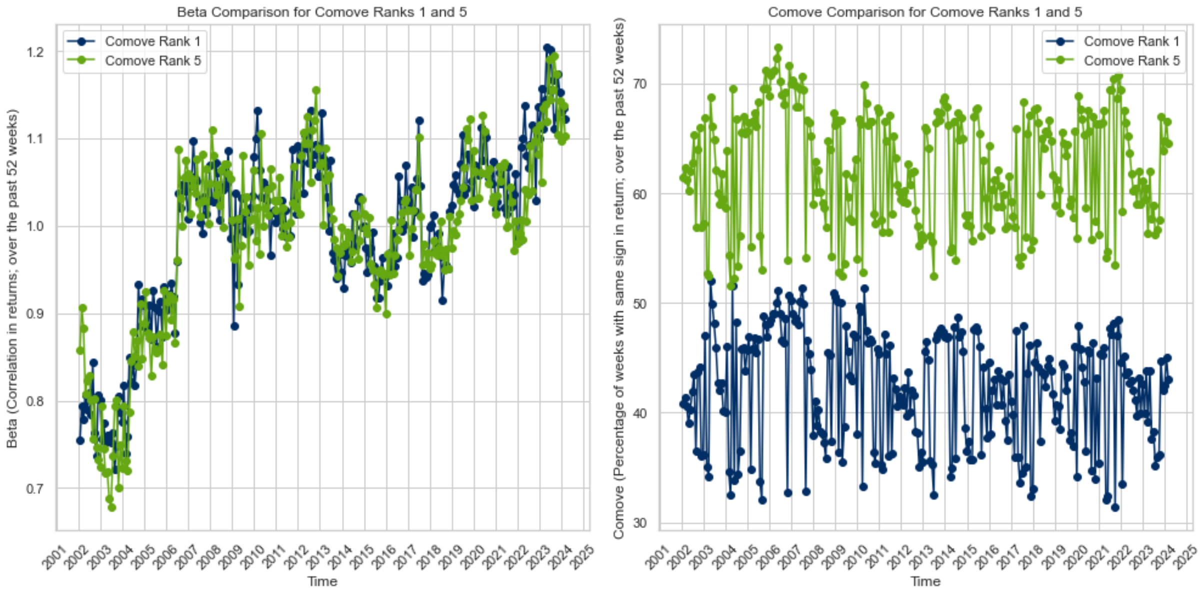

Figure 1 - Average Beta and Frequency of Comovement for Portfolios with Comove rank 1 and 5 over Time.

3.3 Autocorrelation

An Autoregressive (AR) process is a stochastic time series model where the current value of the series is derived from its preceding values. Specifically, in an AR(p) model, the current value depends on the previous p values as expressed by the equation: $Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \epsilon_t$. The determination of p, the number of lag terms, for the return variable will be established through various methodological approaches.

Firstly, the (partial) autocorrelation function of portfolio's with comove rank 1 are depicted in Figure 4 of Section 7. The functions for portfolios with other comovement ranks exhibit similar characteristics. Notably, even at a lag of 1, the values barely exceed the 95% confidence interval. These observations suggest that an AR(1) model might be adequate for modelling this time series data. Secondly, Andrews (1991) compares different methodologies for determining the appropriate number of lags. This approach recommends employing model selection criteria to ascertain the optimal lag length. Information criteria such as the Bayesian Information Criterion weigh model fit against model complexity, in this context, the number of lags, to identify the most suitable model. This method further supports the use of only one lag.

Due to the presence of autocorrelation, standard Ordinary Least Squares estimators are not suitable for regression analysis. Newey-West estimators (Newey & West, 1986) will be used in regression with the correct number of lags (p = 1) to correct for the time-dependency of returns in the dataset.

4 Empirical Results: Frequency of Comovement as an Unexplained Return Premium

4.1 Main Results

A summary of the main results is given in Table 3 of Section 8.

4.1.1 Relationship between Excess Portfolio Return and Comove Rank

In the following section, a nuanced correlation between returns and comovement rankings is observed, although not statistically significant. The methodology involves examining the average return of portfolios based on their comovement rank (i) during a specific month (t) and adjusting this return by subtracting the risk-free rate for the same period (t). This process derives the excess return for each portfolio of a given comovement rank (i) in each month (t).

Figure 5 presented in Section 7 illustrates the temporal fluctuations in excess returns for portfolios at the extremes of the comovement ranking (Rank 1 and Rank 5). Overall, portfolios in Rank 5 exhibit higher peaks and more pronounced troughs, suggesting a greater volatility to market dynamics compared to Rank 1. Portfolios in Rank 1 show stronger performance during financial crises, potentially benefiting from their stability in such adverse market conditions. Despite this, there appears to be an overall marginally higher return for portfolios in Rank 5. Further examination of Figure 2, which illustrates the cumulative average excess return for portfolios within these ranks over time, more clearly reveals a return premium for portfolios with higher comovement.

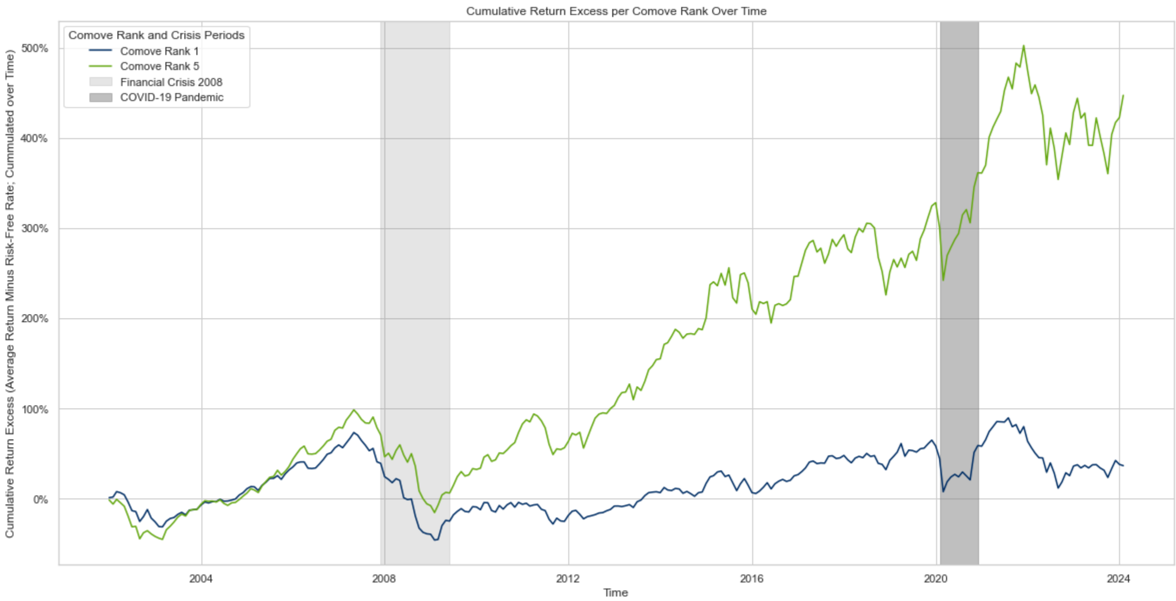

Figure 2 - Cumulative Average Return Excess for Comove Rank 1 and 5 over Time.

Over the analyzed period, portfolios with Comove Rank 1 achieved a monthly excess return of 0.28%, while those in Comove Rank 5 attained a monthly excess return of 0.78%. Therefore, portfolios with higher comovement rankings outperformed those with lower rankings by an average of 0.50% per month. Despite this, regression analysis using a dummy variable (highestComove_dummy) to compare Comove Ranks 1 and 5, adjusted for serial correlation with Newey-West estimations with a single lag, showed that the monthly difference of 0.50% between the ranks is not statistically significant. The high p-value of 0.1441 indicates that one cannot reject the null hypothesis, which posits no significant difference in return premium between the two comovement ranks.

Traditional testing methodologies, such as regression analysis, might inadequately capture the full spectrum of the positive relationship between Comove and expected return excess. This inadequacy stems from their tendency to only compare the returns of the most extreme portfolios (Comove ranks 1 and 5), thereby overlooking the nuances present across the intermediate Comove ranks. Patton and Timmermann (2010) address this limitation by introducing nonparametric tests specifically designed to detect monotonic relationships. By implementing 1000 bootstrap replications and employing a block size of 5 to adjust for autocorrelation (given the lag of one and the monthly allocation of five comovement ranks), the resulting p-value of 0.093 is sufficient to affirm the alternative hypothesis of a monotonically increasing relationship between comovement rank and average portfolio excess returns. This hypothesis can also be accepted when using 10000 bootstrap replications on a 10% significance level (p-value of 0.078).

4.1.2 Carhart's Factor Model Adjustment

The inconclusive results presented in the preceding section raise questions about the potential influence of other variables on the excess returns of portfolios, which might subsequently skew the findings. In response, a regression analysis adhering to the 4-Factor Model (Carhart, 1997) is conducted. This analysis employs Newey-West estimators with one lag, utilizing the following equation:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,M} * \left(R_{M,t} - R_{f,t}\right) + \beta_{i,SMB} * SMB_t + \beta_{i,HML} * HML_t + \beta_{i,UMD} * UMD_t + \epsilon_{i,t}$$

In this equation, $R_{i,t}$ represents the average return of portfolio i in month t, adjusted by the risk-free rate $R_{f,t}$ at that time. The model posits that excess returns can be explained through four factors: market premium, size (small-minus-big), value (high-minus-low), and momentum (up-minus-down) within month t. Definitions of data and sources for the factor data are detailed in Appendix A.

The regression intercept α_i captures any abnormal return premiums that are not accounted for by the other factors in the model. Empirical results reveal that portfolios within the lowest comovement rank (Comove Rank 1) garnered a monthly alpha of 0.16%, while those classified in Comove Rank 5 achieved a higher monthly excess return of 0.61%. The alpha for the high-low portfolio strategy based on comovement is therefore computed at 0.45% per month, translating to a yearly return of 5.41%. This alpha is statistically significant at the 10% level, with a p-value of 0.0904, suggesting that even after adjusting for the Carhart four factors, the long-short strategy predicated on comovement yields significant excess returns.

4.1.3 High-Low Comove Strategy

Regressions pertaining to the high-low strategy are conducted on a monthly basis, using Newey-West estimators with one lag. In the prior approach, five separate estimations were performed each month, one for each comovement rank, where the excess return was calculated as the average return of the portfolio at each respective rank minus the risk-free rate. Currently, the methodology has been streamlined to a single estimation per month. Here, the excess return is computed as the average return of the portfolio at rank 5 in month t minus the average return of the portfolio at rank 1 in the same month. The subtraction of the risk-free rate is omitted in this new approach as it is inherently integrated within the returns of both components, essentially forming a zero-cost portfolio. In layman's terms, this adjusted return reflects the outcome of a strategy where one would consistently purchase stocks with high comovement and sell those with low comovement. This strategy is analysed not only through the previously mentioned dummy variable approach but also by calculating the monthly alpha across various factor models. This revised method further analyses the differential performance attributed to stocks according to their comovement ranks.

In this analysis, a range of alternative factor models that have been identified in the literature are incorporated. Definitions of data and sources for the factor data are detailed in Appendix A. The results are detailed in Panel B of Table 3 in Section 8. The table organizes the results as follows: in the first (fourth) row, the initial findings using only the dummy variable (Carhart (1997) four-factor alpha) are repeated. Subsequently, the second and third rows are dedicated to the estimations based on the Capital Asset Pricing Model (Sharpe, 1964) and the three-factor model (Fama & French, 1993), respectively. In the final row, the estimation is extended to include the five-factor model (Fama & French, 2015). These new models (CAPM, 3F, and 5F) demonstrate a return premium between 6.77% and 10.59% per year, all achieving statistical significance at the 1% level.

Furthermore, the analysis is expanded in other rows to include additional factors beyond the traditional Carhart (1997) four factors. These include the quality-minus-junk factor (Asness et al., 2017), the betting-against-beta strategy (Frazzini & Pedersen, 2014), carry (Koijen et al., 2016), and seasonality effects (Keloharju et al., 2016). While these extended factors contribute to the robustness of the model, the significance acceptance level for the original four-factor model and its extensions predominantly remains at the 10% threshold. In the robustness analysis, the elevated p-values associated with the four-factor model and its extensions are further examined.

To provide a more detailed analysis of the alpha, Carhart alpha's on a monthly basis are computed. To accomplish this, the estimated coefficients derived from the regression analysis are utilized. By multiplying these coefficients with the corresponding monthly four factors and subtracting the sum of these products from the average return of the high-low portfolio for each month, the alpha per month is derived. This controlled return premium of the high-low comove strategy per month is visually illustrated in Figure 3.

In comparison, the cumulative alpha over time for a high-low beta strategy is also depicted. Instead of sorting stocks based on their beta values first and then on their comove values, the order is reversed. As seen on Figure 6 in Section 7, this alteration results in portfolios characterized by relatively stable comove across various portfolios, while beta exhibits significant variation. The high-low beta portfolio entails selling stocks with high beta and purchasing stocks with low beta. In contrast to the high-low comove strategy, this strategy yields a negative cumulated return premium over time, even after adjusting for the Carhart (1997) four factors.

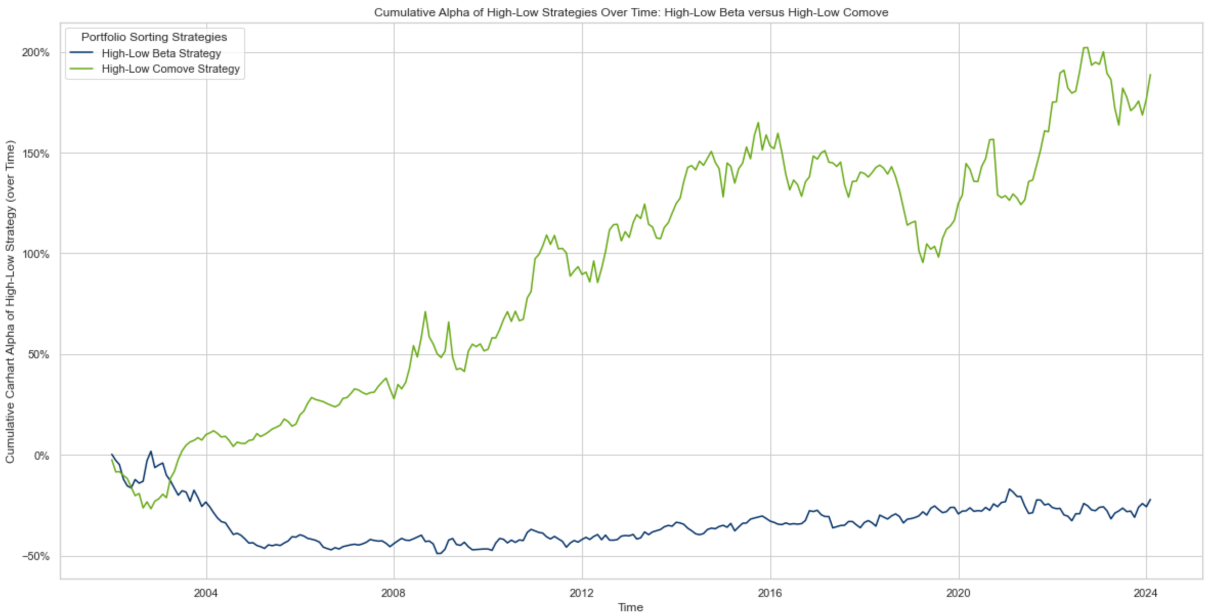

Figure 3 – Cumulative Carhart (1997) Alpha of High-Low portfolio over time: double-sorting on beta first and comove second (Comove strategy) versus double-sorting on comove first and beta second (Beta strategy).

4.1.4 Sample Split

A sample split of the full sample into January 2002 – December 2012 and January 2013 – February 2024 reveals that the return premium is stronger in the earlier subsample, as illustrated in Figure 7 in Section 7. Analysis employing the 4-factor model (Carhart, 1997) and its extensions for the latter subsample (2013-2024) yielded results that were notably low and statistically insignificant. Contrarily, the 5-factor model (Fama & French, 2015) demonstrated statistical significance at the 1% level across the entire dataset and both subsamples. Specifically, it recorded a monthly alpha of 1.06% for the period 2002-2012, and 0.65% for the period 2013-2024.

Further investigation is required to explore the temporal trend in the Comove return premium. In contrast to the findings of this study, Ungeheuer & Weber (2020) suggest an increasing trend in Comove premium. Their research underscores that the American Comove return premium for the period 1989-2015 surpasses that of the 1963-1988 timeframe. This study did not include years before 2002, which are mostly part of their earlier subsample. Additionally, Ungeheuer and Weber (2020) did not analyze the years after 2015, during which this study finds a decreasing trend. It is possible that the Comove premium follows a U-shaped pattern.

4.2 Robustness Tests

4.2.1 Alternative Factor Measures

In the main results, it is observed that the Carhart four-factor model and its extensions exhibit relatively less significance compared to other factor models. This section explores whether alternative data sources for the four factors could enhance the robustness of findings in this paper. Comprehensive definitions of these alternative factor measurements are delineated in Appendix A. Firstly, rather than employing a precomputed market premium $(R_m - R_f)$, it is recalculated independently using the calculated monthly market return of the EUR 600 index, minus the risk-free rate in Europe. The risk-free rate can be proxied by the Euro Overnight Index Average (EONIA) rates for the months up to October 2019. From October 2019 onwards, the Euro Short-Term Rate (€STR) becomes the relevant benchmark. All return indexes are retrieved from DataStream software. Secondly, Asness and Frazzini (2011) underscore the diverse methodological choices involved in constructing the value (High-minus-Low) factor. In their seminal work, "The Devil in HML's Details," they introduce an alternative way of measuring the value factor. Lastly, the trend factor (Moskowitz et al., 2011) exploits the momentum effect over longer periods. It is pertinent to note that this trend factor is considered an additional factor rather than a substitute for the traditional momentum factor (UMD).

Table 4 in Section 8 presents the results. Similar to the main results, the comove premium decreases over time for all alternative factor measures. The four-factor model with an estimated market premium yields a yearly comove return premium of 5.85%. This result closely matches the findings of the initial four-factor model presented in the main results (Carhart, 1997). When considering momentum over a longer time horizon, the comove return premium increases compared to a normal four-factor model (Carhart, 1997): an annual 5.411% versus an annual 6.90%, both at a 1% significance level. When applying the alternative version of the high-minus-low factor in the four-factor model (Carhart, 1997), the yearly comove return premium increases by 3.58% and achieves a higher significance level. In conclusion, controlling for more accurate or comprehensive market information, such as utilizing more historical returns for momentum premiums or an enhanced measure of the value premium, can lead to a better understanding of the true comove premium. These adjustments may indicate that the actual comove premium is higher than previously estimated.

4.2.2 Alternative Index

Although further research is essential, preliminary insights into geographical Comove trends have been facilitated by employing selected national equity indexes and their constituent data to reevaluate the factor model tests as detailed in the main results. This approach aims to provide a broader perspective on the variations observed in Comove return premiums across different regions. The available data on DataStream was limited: a global index was not accessible, and the data comprised only a few national equity indexes, which were themselves restricted. The national indexes used were the Amsterdam Exchange Index (Netherlands), the BEL20 (Belgium), the Cotation Assistée en Continu 40 (France), the Deutscher Aktienindex (Germany), the OMX Stockholm 30 Index (Sweden), and the Swiss Market Index (Switzerland). Data for these national indexes were only available for months starting in early 2000, and typically, these indexes consist of 20 to 40 stocks per month, compared to 600 per month for the STOXX Europe 600 in the main results. Further research is crucial to examine longer time periods, differences between countries, and global trends.

The majority of results were not significant, likely due to the limited number of observations. Figure 8 in Section 7 provides a preliminary glimpse, showing that cumulative Comove return premiums vary, with some countries experiencing significant gains while others see losses. In some cases, the beta high-low strategy performs better. All results for the Comove high-low portfolio are reported in Table 5, Section 8. The only significant result is the 5-Factor model for France, with an annual alpha of approximately 7%, consistent with previous findings.

4.2.3 Alternative Portfolio Aggregation

To ensure portfolios more accurately reflect overall market dynamics, value-weighted portfolios are employed when estimating factor models in the subsequent section. In calculating the portfolio's average return, each stock's return is weighted by its market capitalization. Small-cap stocks often have higher volatility (comove) and potentially higher returns (Banz, 1981), which could inflate the return premium in an equal-weighted analysis. Weighing by market capitalization could lower the overall return premium if smaller stocks previously had a disproportionate impact on the results. The return premium might reflect a more realistic market scenario, especially for institutional investors who invest significant amounts in larger stocks.

However, the results indicate that comove premiums exhibit minimal variation across different weighting schemes. Portfolios associated with higher comovement rankings outperformed those with lower rankings by an average of 0.57% (compared to 0.50% in equal-weighted portfolios) per month, both not statistically significant. After controlling for Carhart (1997) factors, the annual comove premium remains consistent: 5.4119% for equal-weighted portfolios and 5.4135% for value-weighted portfolios, both significant at the 10% level. The CAPM (Sharpe, 1964), 3-factor model (Fama & French, 1993), and 5-factor model (Fama & French, 2015) demonstrate a return premium ranging from 6.77% to 10.59% per year for equal-weighted portfolios, and from 7.60% to 11.10% for value-weighted portfolios, all statistically significant at the 1% level.

4.2.4 Controlling with Fama and MacBeth Regressions

To provide a clear picture of the factor effects both across assets and over time, Fama and MacBeth regressions (1973) are employed. Cross-sectional regression techniques, like Fama and MacBeth regressions, facilitate the examination of individual stocks rather than aggregating them into portfolios. For each month t, the regression equation for month t is:

$$R_{i,t} = \alpha_{0,t} + \beta_{1,t} * F_{1,i,t} + \beta_{2,t} * F_{2,i,t} + \cdots + +\beta_{k,t} * F_{k,i,t} + \epsilon_{i,t}$$

Here, $F_{j,i,t}$ are the factor scores for factor j for stock i in month t and $\beta_{j,t}$ are the coefficients estimated from each monthly cross-sectional regression. The intercept $\alpha_{0,t}$ represents the return that is not explained by the factors.

After performing the cross-sectional regression for each month, the average of the estimated coefficients $\beta_{j,t}$ is calculated across all time periods T:

$$\bar{\beta}_j = \frac{1}{T} * \sum_{t=1}^{T} \beta_{j,t}$$

The t-statistics, which are used to assess the significance of the average coefficients $\bar{\beta}_j$, are calculated using Newey-West (1986) standard errors (with one lag and a Barlett (1955) weighting function). This adjustment method addresses potential autocorrelation and heteroscedasticity in the regression residuals.

Detailed descriptions of all variables related to individual stocks are provided in Appendix B. This study explores the relationship between the return of an individual stock at time t and a set of independent variables in month t, based on data in earlier periods. The **primary variables** used in the Fama & MacBeth regressions reflect those utilized in the portfolio analysis of the four-factor model (Carhart, 1997). The unexplained premium (Comove) and the market risk premium (beta) for an individual stock are computed using the same methods as those used for sorting stocks into portfolios. The natural logarithm of market capitalization represents the size of an individual stock, whereas the natural logarithm of the book-to-market ratio indicates the stock's value. Momentum is captured by the stock's return in the year preceding month t.

4.2.4.1 Other Measurements of Dependency and Volatility

Additionally, it is explored whether the comovement premium can be explained by other measures of market dependency and volatility.

Firstly, measures of **asymmetric systematic risk** are considered, indicating that investors may receive a return premium based on how stocks perform under specific market conditions. Downside and upside beta (Chen et al., 1986) specifically examine how an asset's returns correlate with market returns during market downturns and upturns, respectively. Lower and upper tail dependence (Chabi-Yo et al., 2017) delve deeper into how assets behave relative to the market under extreme conditions. Lower tail dependence evaluates the correlation of an asset's returns with the market during significant downturns, providing insight into the asset's performance during severe market crashes. Similarly, upper tail dependence looks at the correlation of returns during substantial market upswings.

Secondly, accounting is done for measures of **idiosyncratic risk**, which are unique to individual stocks and not attributable to broader market movements. Idiosyncratic risk and the corresponding return premiums stem from factors specific to a particular company or asset, such as decisions by management, earnings reports, regulatory changes, or technological advancements. For example, Biogen Inc.'s journey toward regulatory approval of their Alzheimer's treatment, Aducanumab, was closely watched by investors. News regarding regulatory meetings, FDA panel reviews, and other relevant updates, whether positive or negative, triggered significant fluctuations in Biogen’s stock price (Wainer, 2024). Idiosyncratic volatility is commonly quantified as the standard deviation of the residuals from a factor model (e.g., in the work of Ang et al. (2006)). Alternatively, Bali et al. (2011) suggest a different measure, taking the maximum and minimum daily returns of the most recent month.

SUMMARY STATISTICS

In the subsequent section, the correlation between and the univariate distributions of the main variables is examined, along with the discussed measurements of upside, downside, and idiosyncratic risk.

Table 7 in Section 8 shows that the average (median) frequency of comovement between individual stock returns and EUR 600 returns is 51.65% (51.92%). This is notably lower than the average (median) comovement frequency observed in the U.S. stock market between individual stock returns and S&P 500 returns, which is 63% (63%) (Ungeheuer & Weber, 2020). The average (median) beta value in this study is 0.9915 (0.9635), while the average (median) beta in the U.S. market is 0.9241 (0.8800). The data suggest that the European market exhibits lower comovement and slightly higher beta values on average compared to the U.S. market.

Correlation between variables is presented in Figure 9 of Section 7. Comove exhibits low correlation with Beta (0.01), suggesting that the comovement of stock returns with the market does not necessarily parallel systematic risk as measured by Beta. Among the primary variables, Momentum exhibits the strongest correlation with Comove (0.15), suggesting a potential connection between stocks that maintain momentum and their tendency to move with the market. There is a close relationship between Downside and Upside Beta, which both also have correlation with Beta, LTD, and UTD. The high correlation between LTD and UTD suggests that stocks vulnerable to extreme losses are also likely to experience extreme gains. Idiosyncratic Volatility, Min, and Max are closely correlated, yet they show no significant correlation to Comovement. Figure 10 and Figure 11 in Section 7 further demonstrate that while traditional measures of (asymmetric) systematic or idiosyncratic risk display similar trends over time, the frequency of comovement presents a different pattern.

REGRESSION RESULTS

The complete results from the Fama and MacBeth regressions, incorporating the main variables along with alternative measures of dependency and volatility, are detailed in Section 8, Table 8. The comove premium retains statistical significance at the 1% level even after accounting for the set of variables included in this section. Interestingly, Beta consistently exhibits a negative coefficient across the analyses. Averaged R-squared is around 12% for different models, almost double of the different R-squared found by Ungeheuer and Weber (2020).

Initial results are presented for the main variables. Figure 12 in Section 7 illustrates substantial volatility in the comove return premium over the analyzed period, even after accounting for primary variables. Notably, the comove premium experiences pronounced fluctuations during periods of financial instability such as the financial crisis in 2008 or the Covid-19 pandemic in 2020. This variability indicates that the extent to which individual stocks move in conjunction with the broader market fluctuates significantly over time. Such observations are consistent with empirical evidence suggesting that beta, a measure of systematic risk, also varies over time (Blume, 1971, 1975; Ferson & Harvey, 1991; Jagannathan & Wang, 1996). Aggregated over time, a yearly comove return premium of 7.07% is found at a 1% significant level after controlling for the primary variables that mirror the four-factor model (Carhart, 1997). In contrast, the initial Carhart alpha for the high-low portfolio strategy based on comovement is 5.41% and only statistically significant at the 10% level.

Subsequently, regression analysis is conducted on these main variables, controlling for both upside and downside risk. When measurements of asymmetric market risk are considered, the yearly comove return premium becomes slightly larger (8.64% after controlling for upside and downside beta, and 7.45% after controlling for upper and lower tail dependence) and maintains a statistical significance at the 1% level.

Moreover, the analysis also accounts for idiosyncratic risk. Controlling for idiosyncratic variability yields a comparable annual return premium of 7.01%, which remains significant at the 1% level. When adjustments are made for minimal and maximum returns over the past month, the annual return premium diminishes to 5.57% and achieves a lower level of significance at the 5% level.

In addition to controlling for upside, downside, and idiosyncratic risk, this regression analysis considers other metrics related to dependency and volatility. Specifically, it also adjusts for **liquidity risk**. Gervais et al. (2001) discovered that stocks with more trading activity—quantified by their turnover ratio—are linked to a return premium. They argue that increased trading activity raises a stock's visibility, which subsequently boosts its demand. After controlling for trading activity, a yearly comove premium is 7.11% observed, statistically significant at the 1% level. On the flip side, there may be a liquidity premium for those investing in stocks that are more expensive or challenging to trade (i.e., more illiquid). Amihud (2002) introduces an illiquidity ratio and demonstrates that stocks with a higher ratio are generally linked to increased expected returns. The Amihud illiquidity ratio demonstrates a modest yearly return premium of 0.10%, and it also fails to exhibit a consistent pattern of coefficients for the other variables compared to the models discussed above.

4.2.4.2 Other Benchmarks, Fixed Effects and Skipped Month

Results discussed in the following section are summarized in Table 9, Section 8. The coefficient for Comove is positive across different models but only statistically significant in the model with 5-factor (Fama & MacBeth, 1973) coefficients and the model with alternative Comove calculation. Beta consistently shows a negative coefficient across all models, suggesting that higher market sensitivity measured by beta correlates with lower returns instead of higher returns.

OTHER BENCHMARKS

The four-factor model (Carhart, 1997) is mirrored in this regression analysis, but with a division of the momentum factor into three segments: long-term momentum (analogous to the trend factor at the portfolio level), medium-term momentum (previously referred to simply as momentum), and short-term momentum. This yields a small return premium of 0.86% annually, although not significant.

In the spirit of the five-factor model (Fama & French, 2015), individual stocks are tested for operating profitability (analogous to the Robust-Minus-Weak factor at the portfolio level) and investment (analogous to the Conservative-Minus-Aggressive factor at the portfolio level) as well. A remarkably large return premium of 18.37% per year is observed at the 1% significance level. In the traditional portfolio regression, the five-factor model also yielded the largest return premium (10.59% annually) among various factor models.

FIXED EFFECTS

The four-factor analysis is refined by including fixed effects related to industries, stock exchanges, and size deciles of stocks to account for variations in return premiums. Return premiums across industries are known to differ. For instance, Fama and French (1997) noted significant differences in cost of equity and beta across industries. Additionally, Banz (1981) identified a "size effect" where smaller firms tend to have higher average returns than larger ones. Hou and van Dijk (2019) indicate that despite seeming to vanish post-1980s, the size effect persists in more recent years. A return premium of 3.20% per year is detected, albeit not significant. Remarkably, in comparison to other factor models, this independent variables in this model explain a substantial proportion of variance in the returns (R^2 = 48,52%).

SKIPPED MONTH

Finally, a one-month gap is introduced between the period in which returns are used to calculate comovement and the prediction period for the returns. This is done to prevent lookahead bias, ensuring that predictions are based solely on information that would have been available to investors at the time. The comove premium is statistically significant at the 1% level but is modest (0.64% annually), indicating that comove is largely driven by returns of the last month. This is in contradiction to the work of Ungeheuer and Weber (2020), in which the comove return premium increased.

4.2.4.3 Varying the Comove Measure and the Sample

The results discussed in the subsequent section are consolidated in Table 10 of Section 8.

VARYING THE COMOVE MEASURE

To eliminate biases from specific data selections and methodologies, the calculation of the Comove variable is modified. Instead of relying on the last 52 weekly returns from stocks and the index, the analysis incorporates the last 32 monthly or 260 daily returns. The return premiums for these alternative measures are modest and lack substantial statistical significance. Additionally, the weekly returns of stocks are now compared against the EUR50 index rather than the EUR600. The return premium is fairly small (0.083% annually) and significant at the 1%.

VARYING THE SAMPLE

Stocks from the London Stock Exchange (LN) within the lowest market capitalization decile and those with an absolute return index below 5 euros at the end of the month are excluded from the analysis to minimize the influence of outliers. These outliers, characterized by their low market size or extremely low-price levels, may exhibit high volatility or unique financial conditions that are not reflective of broader market trends. Initially, the dataset contained 159,000 individual stocks, with 45,852 listed on the London Stock Exchange. Euronext Paris follows as the second most common exchange with about 21,399 stocks, approximately half the number from the London exchange. This exclusion of the Londen Stock Exchange is essential to ensure the analysis accurately captures general market behaviours, providing robust insights across different exchanges. Following the exclusion of these stocks, a similar return premium of 7.02% is observed, which is statistically significant with a p-value of less than 0.001.

Similar to the main analysis, a sample split of the full sample into January 2002 – December 2012 and January 2013 – February 2024 is done. In the first half of the dataset, a return premium of 17.74% is observed, statistically significant at the 1% level. Conversely, the latter half of the sample displays a negative return premium that lacks statistical significance. This pattern corroborates observations made during the sample split reported in the main results.

5 Conclusion

5.1 Key Findings

FREQUENCY OF COMOVEMENT AND BETA IN DIFFERENT MARKETS. The average (median) frequency of comovement between individual stock returns and EUR 600 returns is 51.65% (51.92%). The average (median) beta value is 0.9915 (0.9635). The European market shows lower comovement and marginally higher beta values on average compared to the U.S. market (Ungeheuer & Weber, 2020). Moreover, the correlation between comovement and beta is negligible (0.01), implying that the comovement of stock returns with the market does not necessarily align with systematic risk as measured by beta. High-low strategies produced a positive cumulative return for double-sorting on comovement and a negative cumulative return for double-sorting on beta after accounting for the Carhart four factors (1997). Contrary to frequency of comovement and the Capital Asset Pricing Model (Sharpe, 1964) predictions, beta exhibited a significant negative coefficient in almost all Fama and Macbeth regressions.

INITIAL RELATIONSHIP BETWEEN FREQUENCY OF COMOVEMENT AND EXPECTED RETURN. Initial findings concerning returns support our first hypothesis. Portfolios with higher comovement ranks achieved higher average excess returns. Rank 1 portfolios had a monthly excess return of 0.28%, while Rank 5 portfolios had 0.78%, resulting in an average outperformance of 6.05% per year. Regression analysis with Newey-West adjustments indicated that the difference in return premium between the comovement ranks was not statistically significant (p-value: 0.1441). Employing the same high-minus-low comovement strategy (i.e., buying the portfolio with the highest comovement frequency and selling the portfolio with the lowest comovement frequency), Ungeheuer and Weber (2020) found a return premium of 4.28% per year. Patton and Timmerman monotonicity tests (2010) confirmed increasing returns from low to high comovement ranks (p-value: 0.093 with 1,000 bootstraps and 0.0782 with 10,000 bootstraps).

CONTROLLING FOR FACTORS. Controlling for factors further confirmed our initial hypothesis. In first place, high-low strategy yielded a yearly return of 5.41% after controlling for Carhart's four factors (1997), significant at the 10% level (p-value: 0.0904). Ungeheuer and Weber find a similar 5.79% return premium. The comovement-based strategy demonstrated robust performance across various factor models (CAPM (Sharpe, 1964), Fama-French three-factor (1993), and five-factor models (2015)), with annual return premiums ranging from 6.77% to 7.44% and 10.59%, all statistically significant at the 1% level. Less significant return premiums were observed when incorporating additional factors such as quality-minus-junk (8.50%), betting-against-beta (5.42%), carry (6.87%), and seasonality (7.74%). Ungeheuer and Weber (2020) found the return premium remained statistically significant, ranging between 3.49% and 6.16% when controlling for various factor models. Secondly, value-weighted portfolios were compared to equal-weighted ones, showing minimal variation in comovement premiums (7.60% for the CAPM, 8.15% for the three-factor model, 11.09% for the five-factor model, all 1% significant, and 5.41% for the four-factor model with 10% significance), suggesting robustness across different weighting schemes. Lastly, cross-sectional regression analysis also confirmed the statistical significance of the comovement premium after accounting for factor models. Initially, an annual return premium of 7.07% was observed, significant at the 1% level, after controlling for primary variables reflective of the four-factor model (Carhart, 1997). The model was then adjusted to include different momentum segments and the variables of the five-factor model (Fama & French, 2015), which produced varying return premiums: 0.86% per year (not significant) and 19.74% per year (significant at the 1% level).

CONTROLLING FOR OTHER MEASURES OF VOLATILITY AND DEPENDENCY. Fama and Macbeth regressions (1973) demonstrated that the comovement return premium was robust against other measures of dependency and volatility, all at the 1% significance level. Including asymmetric risk measures (upside and downside beta, tail dependence) slightly increased the comovement return premium compared to the initial four-factor model of the Fama and Macbeth regressions (8.64% for upside and downside beta and 7.54% for upper and lower tail dependence). Controlling for idiosyncratic risk provided a comparable annual return premium of 7.01% (idiosyncratic volatility) and 5.57% (min and max return of the past month, significant at the 5% level). Liquidity risk adjustments showed that stocks with higher trading activity were linked to a return premium 7.11%. On the flip slide, stocks that are harder to sell may also be linked to a return premium. The Amihud illiquidity ratio (2002) demonstrated a modest yearly return premium of 0.10%, without a consistent pattern for other variables.

VARYING MEASUREMENTS OF DIFFERENT VARIABLES. Employing alternative data sources and factor measurements confirmed the main results, with some adjustments indicating a higher actual comovement premium than initially estimated for the four-factor model (5.85% for an estimated market premium, 6.90% for an additional trend factor, and 8.99% for an adjusted value factor). In the Fama and Macbeth regressions, the frequency of comovement was measured using different methods. Introducing a one-month gap between the period in which returns are used to calculate comovement and the prediction period for returns resulted in a modest but statistically significant comovement premium of 0.64% annually at the 1% level. This suggests that comovement is largely driven by the returns of the last month, contrary to Ungeheuer and Weber (2020), who found an increased comovement return premium. When using the last 32 monthly or 260 daily returns instead of the last 52 weekly returns from stocks and the index, the return premiums were modest and lacked substantial statistical significance. Additionally, comparing weekly returns of stocks against the EUR50 index rather than the EUR600 yielded a small return premium (0.083% annually), significant at the 1% level.

VARYING THE SAMPLE. Including fixed effects for industries, stock exchanges, and size deciles in the Fama and Macbeth regressions improved the model's explanatory power but did not yield a significant return premium. Excluding stocks from the London Stock Exchange within the lowest market capitalization decile and those with an absolute return index below 5 euros at the end of the month, a return premium of 7.02% was observed for the four-factor model, statistically significant with a p-value of less than 0.001. Preliminary insights into geographical comovement trends using national equity indexes revealed mixed results, with significant findings only for the French market (6.91% for a five-factor model). Ungeheuer and Weber (2020) found a 4.91% premium, while this study identified a 10.59% premium for the same model. Looking into temporal trends, the return premium was stronger in the earlier subsample (2002-2012) compared to the latter period (2013-2024). The five-factor model indicated significant results across both subsamples, with yearly alphas of 12.72% (2002-2012) and 7.81% (2013-2024). In the Fama and Macbeth regressions, a sample split showed a return premium of 17.74% in the first half of the dataset, statistically significant at the 1% level, while the latter half displayed a negative return premium that lacked statistical significance. This partly contradicts Ungeheuer and Weber (2020), who found an increasing trend of comovement premium over time in their 1963-1988 and 1989-2015 subsamples.

5.2 Key Insights

This study, along with the study by Ungeheuer and Weber (2020), highlights several critical insights into the relationship between the frequency of comovement, beta values, and market returns.

Firstly, the European market exhibits a lower comovement frequency and slightly higher beta values compared to the U.S. market, with average (median) comovement at 51.65% (51.92%) and beta at 0.9915 (0.9635). Notably, the correlation between comovement and beta is negligible (0.01), suggesting that comovement with the market does not align closely with systematic risk as measured by beta. Furthermore, high-low investment strategies based on comovement frequency generated positive cumulative returns, whereas similar strategies based on beta produced negative cumulative returns when adjusted for the Carhart four factors (1997). Contrary to the Capital Asset Pricing Model (CAPM) predictions, beta exhibited a significant negative coefficient in nearly all Fama and Macbeth regressions, indicating a complex relationship between beta and returns. These findings underscore the importance of considering comovement frequency as a distinct factor in portfolio construction and risk assessment, beyond traditional beta measurements.

Secondly, a comovement premium exists, demonstrating an annual outperformance of 6.05% for portfolios with high versus low comovement frequency. This premium remains significant after controlling for various factor models, such as the CAPM, Fama-French three-factor, and five-factor models, with annual return premiums ranging from 6.77% to 10.59%, all statistically significant at the 1% level. The comovement-based strategy showed robust performance even when considering alternative factor measures, asymmetric systematic risk, idiosyncratic risk, and liquidity risk, maintaining a premium of around 7% for the four-factor model. The comovement premium is consistent in both equal-weighted and value-weighted portfolios, indicating that smaller stocks do not disproportionately impact this premium. It also remains robust when accounting for fixed effects related to size, industries, and stock exchanges.

Thirdly, methodological, geographical, and temporal differences are observed, indicating the need for further research. Geographically, the comovement premium appears slightly higher in Europe compared to America, though results vary significantly across European countries and are not consistently significant. Temporally, the comovement premium has shown considerable variation, being more pronounced before 2015 and losing significance afterward. Lastly, varying the methodology for measuring comovement significantly impacts the return premium and its statistical significance. These findings suggest that while comovement can be a valuable metric for financial analysis and portfolio management, its effectiveness is sensitive to the specific measurement approach and the temporal and geographical context.

5.3 Suggestions for Future Research

Considering the findings of this paper, questions about **the temporal and geographical disparities in Comove return premiums** may be warranted. To begin with, findings in this paper indicate a decline in Comove return premiums post-2015, while Ungeheuer and Weber (2020) identified an upward trend in Comove return premiums from the late 20th century into the early 21st century. Utilizing a five-factor model (Fama & French, 2015), this study reports an annual alpha of 12.71% from 2002 to 2012, diminishing to 7.81% for the period 2013 to 2024 within European markets. In contrast, Ungeheuer and Weber (2020) documented an American return premium of 4.66% annually for 1963 to 1988 and 4.77% for 1989 to 2015. Ungeheuer and Weber (2020) attribute this variation to heightened risk awareness, as evidenced by an increased volume of related articles in the New York Times during the latter period of their analysis. One might speculate that beta, comove, and other dependency measures gained prominence at the beginning of the century, but recently, the attention given to these metrics has reduced to lesser extents. For instance, a brief examination with Google Trends (2024) reveals a downward trend in searches for the term "risk" within the global stock exchange category, as illustrated in of Section 7. Additionally, empirical analyses have demonstrated the instability of related measures, such as beta (Blume, 1975), over time. In conclusion, further investigation is warranted to fully understand the temporal dynamics and underlying causes influencing the Comove return premium.

Furthermore, the European return premiums for a high-low Comove strategy may exceed those reported by Ungeheuer and Weber (2020) for the American market. When adjusting for various factors, European alphas ranged from 5.41% to 10.59% annually during the 2002 to 2022 interval, whereas American alphas varied between 3.49% and 6.16% annually from 1963 to 2015. This discrepancy may suggest that although the market sensitivity of stocks, as indicated by the frequency of comovement or correlation, remains consistent, the compensation for the same market sensitivity could be higher in inherently riskier markets. Structural differences in market dynamics such as liquidity, diversification, and the scale of institutional investments vary between the two regions (Pagano et al., 2001). The U.S. market is often perceived as more stable and less volatile compared to European markets (Tilfani et al., 2020), potentially leading to lower beta premiums due to its perceived economic stability. Analogously, Bartram and Grinblatt (2018) highlight that local market inefficiencies can cause variations in risk premiums, including beta premiums. Regulatory and cultural differences might also contribute to the observed variations in return premiums. Additionally, results varied significantly across European countries and are not consistently significant. Further research is warranted to explore these dynamics more thoroughly.

The thesis reveals a critical finding that the frequency of comovement is a more accurate measure of perceived dependence than traditional correlation. As Ungeheuer and Weber (2020) mention, this finding opens up important questions about the **cognitive processes underlying investors' understanding and use of these measures**. Future research should focus on whether individuals genuinely do not understand the statistical measures of correlation, or whether they find it cognitively easier to use a simple counting heuristic. In the context of behavioral finance, researchers could design experiments to explore the cognitive biases that investors use when evaluating stock dependencies. Such experiments could help determine whether investors' choices are driven by a lack of comprehension of complex dependencies or by a deliberate preference for simpler, more intuitive heuristics.

Moreover, the study highlights that these measures not only assess different aspects of market dependency but also have **different impacts on expected returns**. In Fama and Macbeth regressions (1973) predicting return, all beta coefficients were negative, whereas the frequency of comovement coefficients were positive. Cumulative Carhart's alpha (1997) over time shows profitable results for a high-low comovement strategy while yielding negative results for a high-low beta strategy. This perceived versus actual dependence may explain why beta has not been priced according to the CAPM's (Sharpe, 1964) empirical evidence (Fama & French, 2003). Perhaps the frequency of comovement serves as a more accurate predictor for priced market risk compared to traditional correlation measurement, suggesting its potential utility in asset pricing models. However, the primary critique of beta—that it is based on historical returns and varies over time—also applies to the frequency of comovement.

Finally, the thesis demonstrates that the comovement measure can generate significant excess returns across various factor models. To further **enhance its applicability**, future research should address several gaps. One notable gap is the lack of comprehensive national equity indexes, historical returns before 2000, and factor estimations for the European region. Additionally, it is crucial to investigate the impact of macroeconomic factors on comovement. Researchers should examine how different economic conditions influence the frequency of comovement and how this, in turn, affects stock returns. Extending the analysis of comovement to different asset classes is another promising avenue. Researchers should evaluate whether the comovement measure can be effectively applied to bonds, commodities, and other financial instruments, and assess its efficacy in predicting returns across these asset classes. Furthermore, the relationship between comovement and its most correlated variable, momentum, deserves detailed exploration. Future studies should analyze anomalies when momentum is segmented into short, medium, and long terms. Understanding these patterns could enhance the predictive power of comovement under various market conditions.

6 Bibliography

Aghion, P., Frydman, R., Stiglitz, J., & Woodford, M. (2003). *Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps*. Princeton University Press. https://doi.org/10.2307/j.ctv18zhdvn

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31–56. https://doi.org/10.1016/S1386-4181(01)00024-6

Andrews, D. W. K. (1991). Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation. *Econometrica*, *59*(3), 817–858. https://doi.org/10.2307/2938229

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The Cross-Section of Volatility and Expected Returns. *The Journal of Finance*, *61*(1), 259–299. https://doi.org/10.1111/j.1540-6261.2006.00836.x

AQR Capital Management. (2024a). *Betting Against Beta: Equity Factors Data, Monthly* [dataset]. https://www.aqr.com/Insights/Datasets/Betting-Against-Beta-Equity-Factors-Monthly

AQR Capital Management. (2024b). *Quality Minus Junk: Factors, Monthly* [dataset]. https://www.aqr.com/Insights/Datasets/Quality-Minus-Junk-Factors-Monthly

Asness, C. S., & Frazzini, A. (2011). *The Devil in HML's Details* (SSRN Scholarly Paper 2054749). https://doi.org/10.2139/ssrn.2054749

Asness, C. S., Frazzini, A., & Pedersen, L. H. (2017). *Quality Minus Junk* (SSRN Scholarly Paper 2312432). https://doi.org/10.2139/ssrn.2312432

Baker, M., & Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance*, *61*(4), 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Bali, T. G., Cakici, N., & Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, *99*(2), 427–446. https://doi.org/10.1016/j.jfineco.2010.08.014

Baltussen, G., Swinkels, L., & van Vliet, P. (2019). *Global Factor Premiums* (SSRN Scholarly Paper 3325720). https://doi.org/10.2139/ssrn.3325720

Baltussen, G., Swinkels, L., & Van Vliet, P. (2021). *Global Factor Premiums* [dataset]. Erasmus University Rotterdam (EUR). https://doi.org/10.25397/eur.14237024.v1

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, *9*(1), 3–18. https://doi.org/10.1016/0304-405X(81)90018-0

Barlett, M. S. (1955). *An Introduction to Stochastic Processes with special reference to Methods and Applications* (Issue 332). Cambridge University Press. https://www.semanticscholar.org/paper/An-introduction-to-stochastic-processes%2C-with-to-Bartlett/ffd17dd115f36a873a2ad25a73033f902ddc8369

Bartram, S. M., & Grinblatt, M. (2018). *Global Market Inefficiencies* (SSRN Scholarly Paper 2540216). https://doi.org/10.2139/ssrn.2540216

Black, F. (1972). Capital Market Equilibrium with Restricted Borrowing. *The Journal of Business*, *45*(3), 444. https://doi.org/10.1086/295472

Blitz, D., Falkenstein, E. G., & van Vliet, P. (2013). *Explanations for the Volatility Effect: An Overview Based on the CAPM Assumptions* (SSRN Scholarly Paper 2270973). https://doi.org/10.2139/ssrn.2270973

Blume, M. E. (1971). On the Assessment of Risk. *The Journal of Finance*, *26*(1), 1–10. https://doi.org/10.1111/j.1540-6261.1971.tb00584.x

Blume, M. E. (1975). Betas and Their Regression Tendencies. *The Journal of Finance*, *30*(3), 785–795. https://doi.org/10.1111/j.1540-6261.1975.tb01850.x

Bossaerts, P., & Plott, C. (2004). Basic Principles of Asset Pricing Theory: Evidence from Large-Scale Experimental Financial Markets. *Review of Finance*, *8*(2), 135–169.

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*, *52*(1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Celik, S. (2012). *Theoretical and Empirical Review of Asset Pricing Models: A Structural Synthesis* (SSRN Scholarly Paper 2034376). https://papers.ssrn.com/abstract=2034376

Chabi-Yo, F., Ruenzi, S., & Weigert, F. (2017). *Crash Sensitivity and the Cross-Section of Expected Stock Returns* (SSRN Scholarly Paper 2011746). https://doi.org/10.2139/ssrn.2011746

Chen, N.-F., Roll, R., & Ross, S. A. (1986). Economic Forces and the Stock Market. *The Journal of Business*, *59*(3), 383. https://doi.org/10.1086/296344

Clayton, D. G. (1978). A Model for Association in Bivariate Life Tables and Its Application in Epidemiological Studies of Familial Tendency in Chronic Disease Incidence. *Biometrika*, *65*(1), 141–151. https://doi.org/10.2307/2335289

Constantinides, G. M. (1986). Capital Market Equilibrium with Transaction Costs. *Journal of Political Economy*, *94*(4), 842–862.

DeJong, D. V., & Collins, D. W. (1985). Explanations for the Instability of Equity Beta: Risk-Free Rate Changes and Leverage Effects. *Journal of Financial and Quantitative Analysis*, *20*(1), 73–94. https://doi.org/10.2307/2330678

Enke, B., & Zimmermann, F. (2013). *Correlation Neglect in Belief Formation* (SSRN Scholarly Paper 2263648). https://doi.org/10.2139/ssrn.2263648

Eyster, E., & Weizsacker, G. (2016). *Correlation Neglect in Portfolio Choice: Lab Evidence* (SSRN Scholarly Paper 2914526). https://doi.org/10.2139/ssrn.2914526

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance*, *47*(2), 427–465. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E. F., & French, K. R. (1997). Industry costs of equity. *Journal of Financial Economics*, *43*(2), 153–193. https://doi.org/10.1016/S0304-405X(96)00896-3

Fama, E. F., & French, K. R. (2003). *The Capital Asset Pricing Model: Theory and Evidence* (SSRN Scholarly Paper 440920). https://doi.org/10.2139/ssrn.440920

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010

Fama, E. F., & MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, *81*(3), 607–636.

Ferson, W. E., & Harvey, C. R. (1991). The Variation of Economic Risk Premiums. *Journal of Political Economy*, *99*(2), 385–415.

Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, *111*(1), 1–25. https://doi.org/10.1016/j.jfineco.2013.10.005

French, K. R. (2024a). *Description of Fama/French 5 Factors (2x3) from July 1963—March 2024* [dataset]. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5_factors_2x3.html

French, K. R. (2024b). *Description of Fama/French 5 Factors for Developed Market from July 1990—March 2024* [dataset]. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5developed.html

French, K. R. (2024c). *Monthly Momentum Factor (Mom)* [dataset]. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_mom_factor.html

Friend, I., & Blume, M. (1970). Measurement of Portfolio Performance Under Uncertainty. *The American Economic Review*, *60*(4), 561–575.

Gervais, S., Kaniel, R., & Mingelgrin, D. H. (2001). The High-Volume Return Premium. *The Journal of Finance*, *56*(3), 877–919. https://doi.org/10.1111/0022-1082.00349

Google Searches for the Search Term 'Risk'. (2024). Google Trends. https://trends.google.com/trends/explore?cat=1282&date=all&q=correlation&hl=nl

Gumbel, E. J. (2019). Statistics of Extremes. In *Statistics of Extremes*. Columbia University Press. https://doi.org/10.7312/gumb92958

Hirshleifer, D. A., & Jiang, D. (2010). *A Financing-Based Misvaluation Factor and the Cross Section of Expected Returns* (SSRN Scholarly Paper 972695). https://papers.ssrn.com/abstract=972695

Hou, K., & van Dijk, M. A. (2019). Resurrecting the Size Effect: Firm Size, Profitability Shocks, and Expected Stock Returns. *The Review of Financial Studies*, *32*(7), 2850–2889.

Hou, K., Xue, C., & Zhang, L. (2015). Digesting Anomalies: An Investment Approach. *The Review of Financial Studies*, *28*(3), 650–705. https://doi.org/10.1093/rfs/hhu068

Jagannathan, R., & Wang, Z. (1996). The Conditional CAPM and the Cross-Section of Expected Returns. *The Journal of Finance*, *51*(1), 3–53. https://doi.org/10.1111/j.1540-6261.1996.tb05201.x

Kelly, B., & Jiang, H. (2014). Tail Risk and Asset Prices. *The Review of Financial Studies*, *27*(10), 2841–2871. https://doi.org/10.1093/rfs/hhu039

Keloharju, M., Linnainmaa, J. T., & Nyberg, P. (2016). Return Seasonalities. *The Journal of Finance*, *71*(4), 1557–1590. https://doi.org/10.1111/jofi.12398

Kendall, M. G. (1938). A New Measure of Rank Correlation. *Biometrika*, *30*(1/2), 81–93. https://doi.org/10.2307/2332226

Koijen, R. S. J., Moskowitz, T. J., Pedersen, L. H., & Vrugt, E. B. (2016). *Carry* (SSRN Scholarly Paper 2298565). https://doi.org/10.2139/ssrn.2298565

Laudenbach, C., Ungeheuer, M., & Weber, M. (2019). *How to Alleviate Correlation Neglect* (SSRN Scholarly Paper 3391084). https://papers.ssrn.com/abstract=3391084

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, *47*(1), 13–37. https://doi.org/10.2307/1924119

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, *7*(1), 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x

Merton, R. (1973). An Intertemporal Capital Asset Pricing Model. *Econometrica*, *41*(5), 867–887.

Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2011). *Time Series Momentum* (SSRN Scholarly Paper 2089463). https://doi.org/10.2139/ssrn.2089463

Newey, W. K., & West, K. D. (1986). *A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelationconsistent Covariance Matrix* (SSRN Scholarly Paper 225071). https://papers.ssrn.com/abstract=225071

Pagano, M., Randl, O., Röell, A. A., & Zechner, J. (2001). What makes stock exchanges succeed? Evidence from cross-listing decisions. *European Economic Review*, *45*(4), 770–782. https://doi.org/10.1016/S0014-2921(01)00132-5

Pastor, L., & Stambaugh, R. F. (2001). *Liquidity Risk and Expected Stock Returns* (Working Paper 8462). National Bureau of Economic Research. https://doi.org/10.3386/w8462

Patton, A. J., & Timmermann, A. (2010). Monotonicity in asset returns: New tests with applications to the term structure, the CAPM, and portfolio sorts. *Journal of Financial Economics*, *98*(3), 605–625. https://doi.org/10.1016/j.jfineco.2010.06.006

Reilly, F. K., & Brown, K. C. (2011). *Investment Analysis and Portfolio Management*. Cengage Learning.

Roll, R. (1977). A critique of the asset pricing theory's tests Part I: On past and potential testability of the theory. *Journal of Financial Economics*, *4*(2), 129–176. https://doi.org/10.1016/0304-405X(77)90009-5

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, *13*(3), 341–360. https://doi.org/10.1016/0022-0531(76)90046-6

Sadka, R. (2003). *Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk* (SSRN Scholarly Paper 428160). https://doi.org/10.2139/ssrn.428160

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *The Journal of Finance*, *19*(3), 425–442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Stambaugh, R. F., & Yuan, Y. (2016). *Mispricing Factors* (SSRN Scholarly Paper 2626701). https://doi.org/10.2139/ssrn.2626701

Tilfani, O., Ferreira, P., Dionisio, A., & Youssef El Boukfaoui, M. (2020). EU Stock Markets vs. Germany, UK and US: Analysis of Dynamic Comovements Using Time-Varying DCCA Correlation Coefficients. *Journal of Risk and Financial Management*, *13*(5), Article 5. https://doi.org/10.3390/jrfm13050091

Ungeheuer, M., & Weber, M. (2020). *The Perception of Dependence, Investment Decisions, and Stock Prices* (SSRN Scholarly Paper 2739130). https://doi.org/10.2139/ssrn.2739130

United Nations. (2015). *Transforming our World: The 2030 Agenda for Sustainable Development*. United Nations Department of Economic and Social Affairs. https://sdgs.un.org/publications/transforming-our-world-2030-agenda-sustainable-development-17981

Wainer, D. (2024, April 25). *For Beaten-Down Maker of Alzheimer’s Drug, Good Enough Will Do*. Wall Street Journal. https://www.wsj.com/finance/stocks/for-beaten-down-maker-of-alzheimers-drug-good-enough-will-do-a1d05a65

7 Additional Figures

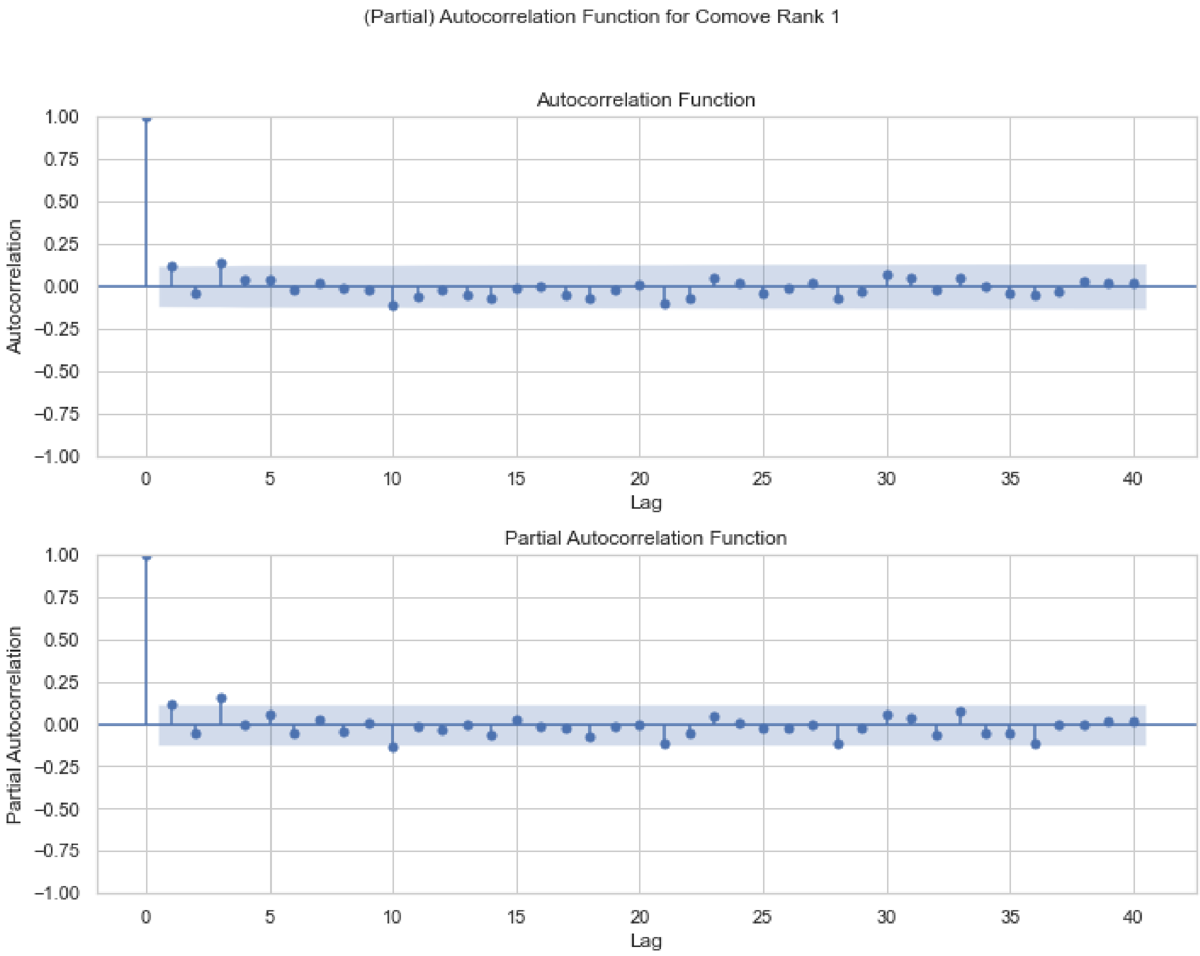

Figure 4 - (Partial) Autocorrelation Function for Portfolio's with Comove Rank 1.

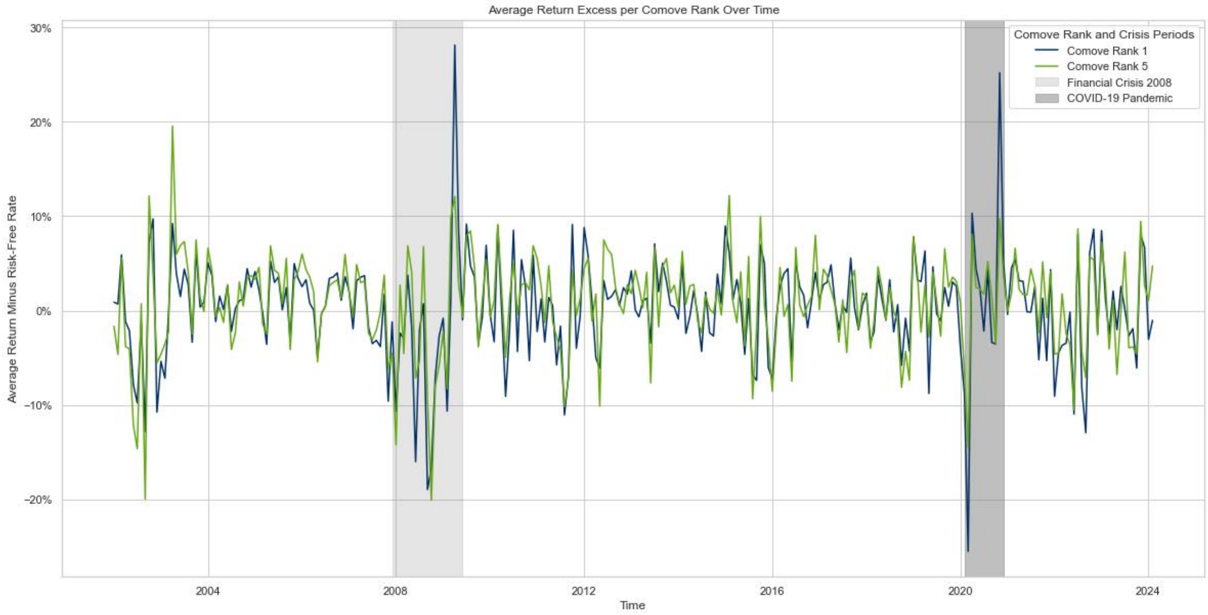

Figure 5 - Average Return Excess for Comove Rank 1 and 5 over Time.

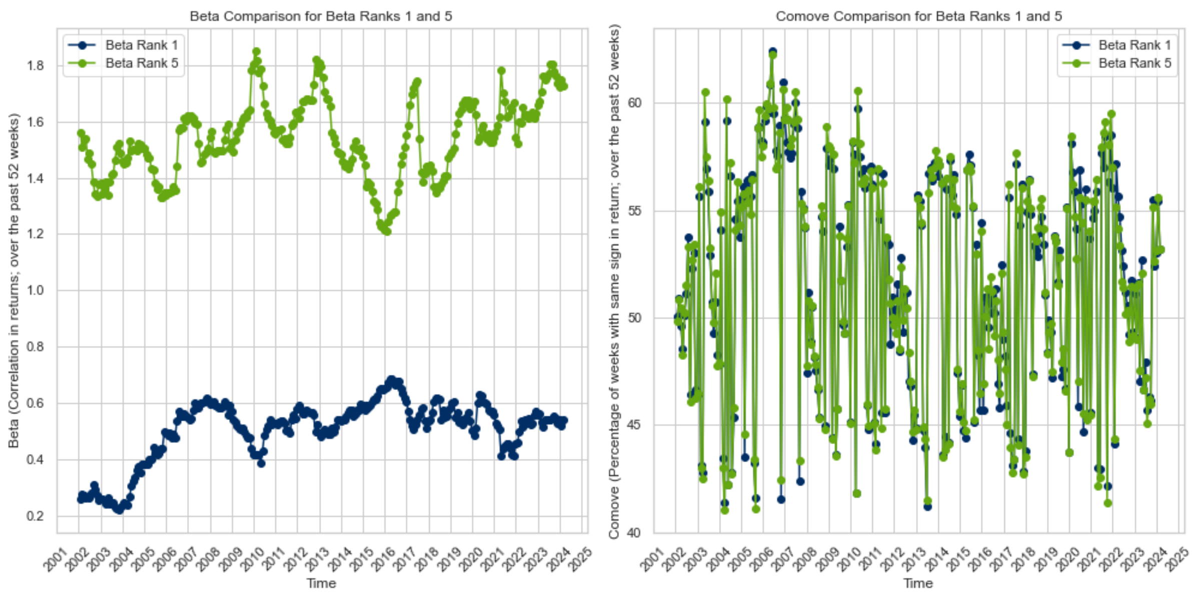

Figure 6 - Average Beta and Frequency of Comovement for Portfolios with Beta rank 1 and 5 over Time.

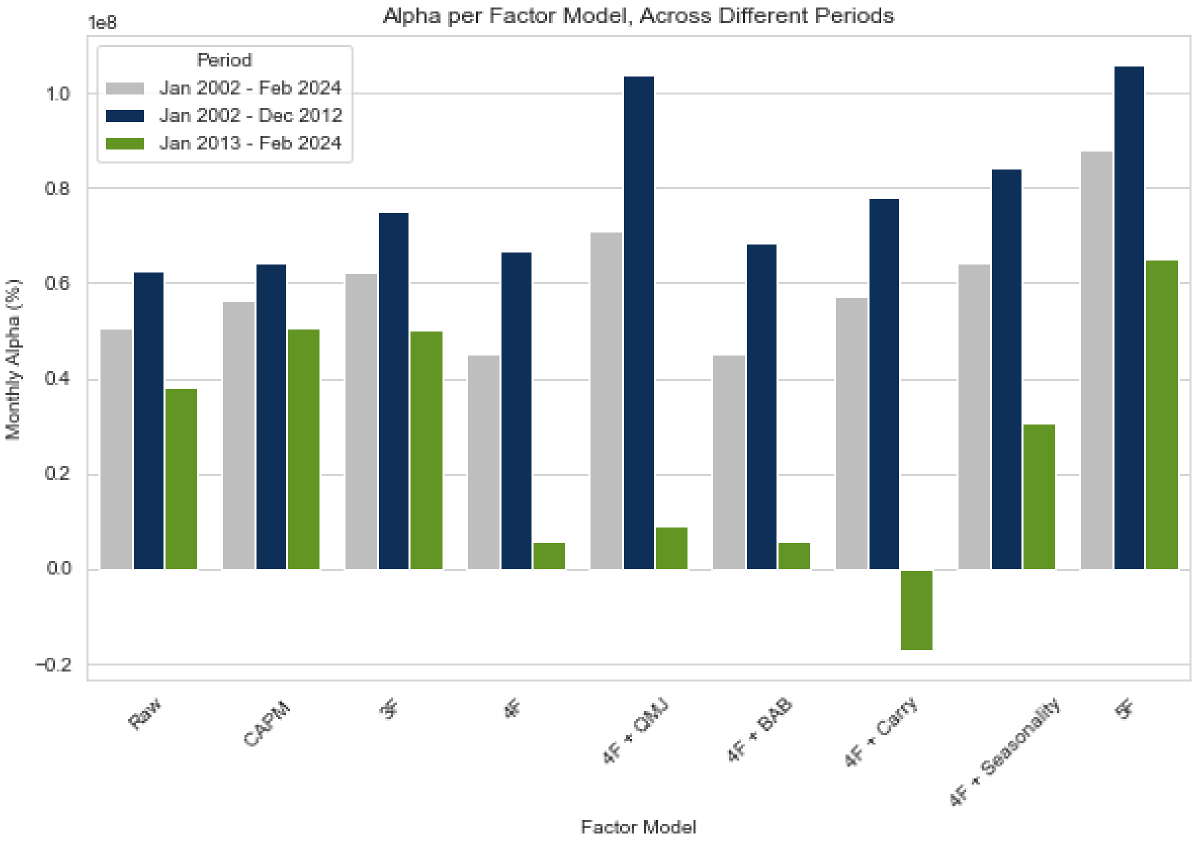

Figure 7 - Estimated Alpha per Factor Model, Across Different Time Periods.

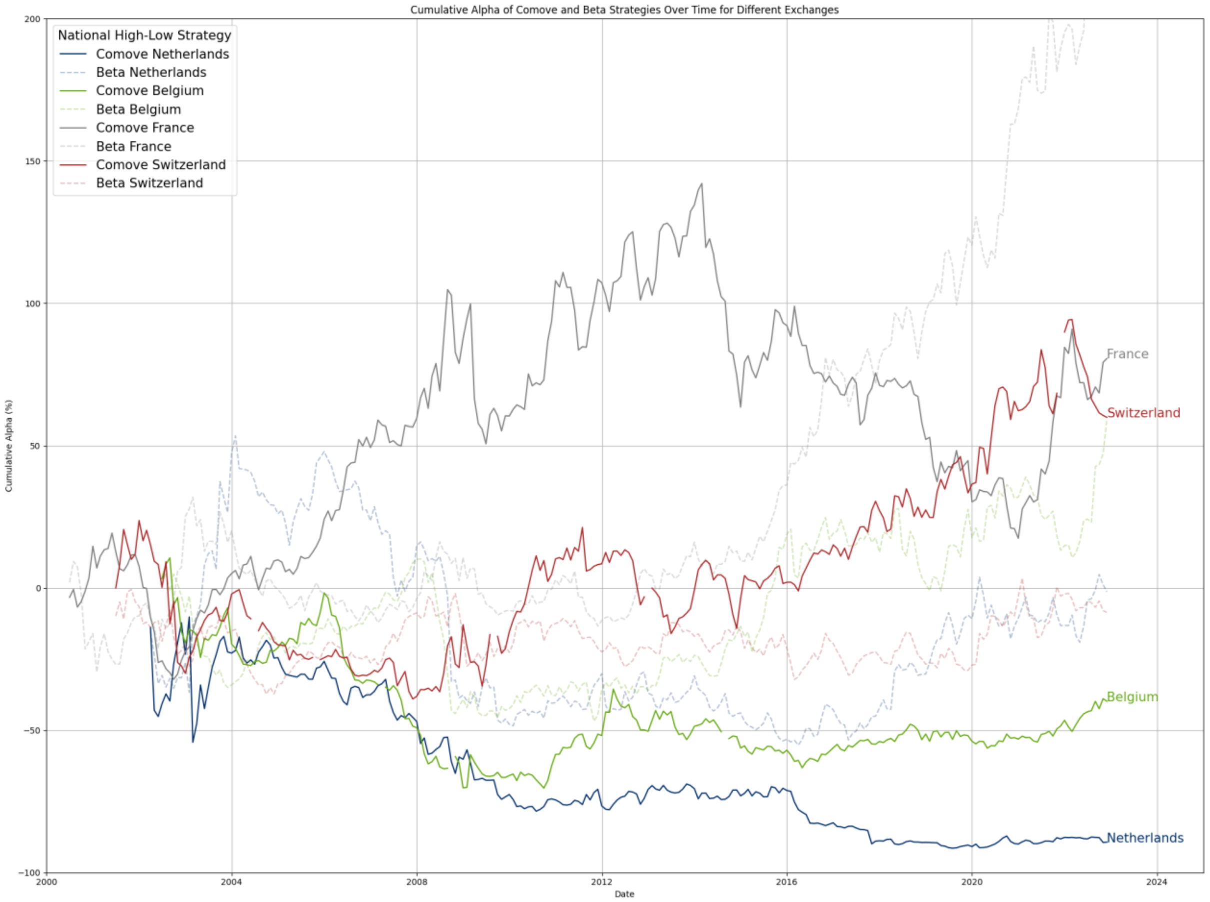

Figure 8 - Cumulative Carhart (1997) Alpha of High-Low portfolio over time for various national indexes: double-sorting on beta first and comove second (Comove strategy) versus double-sorting on comove first and beta second (Beta strategy).

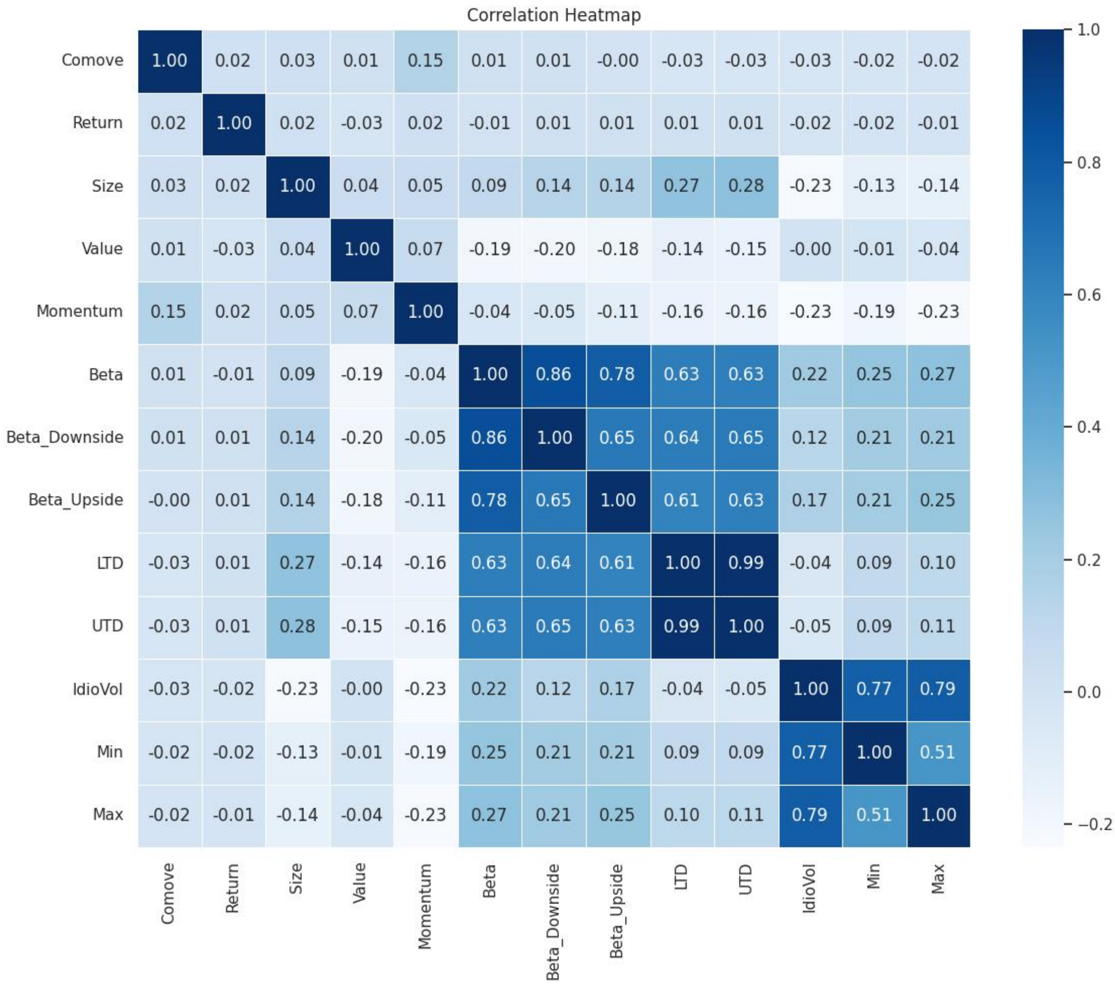

Figure 9 - Correlations between variables of Fama and MacBeth regressions.

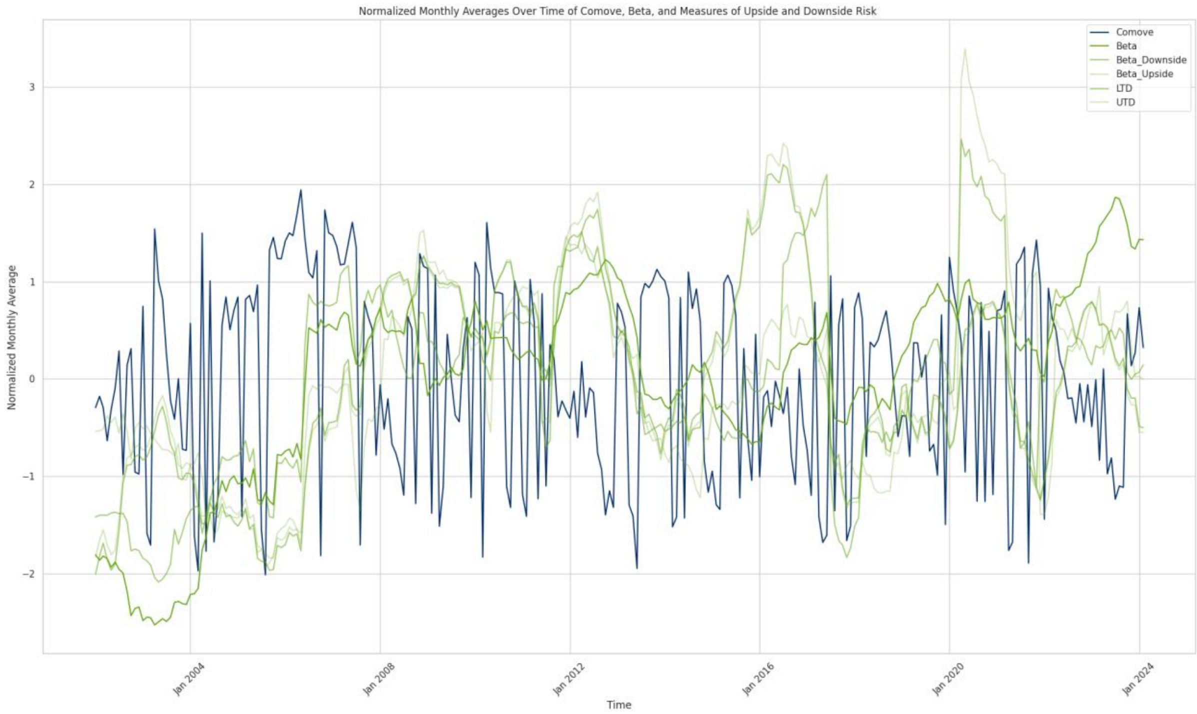

Figure 10 - Normalized Monthly Averages Over Time of Comove, Beta, and Measures of Upside and Downside Risk.

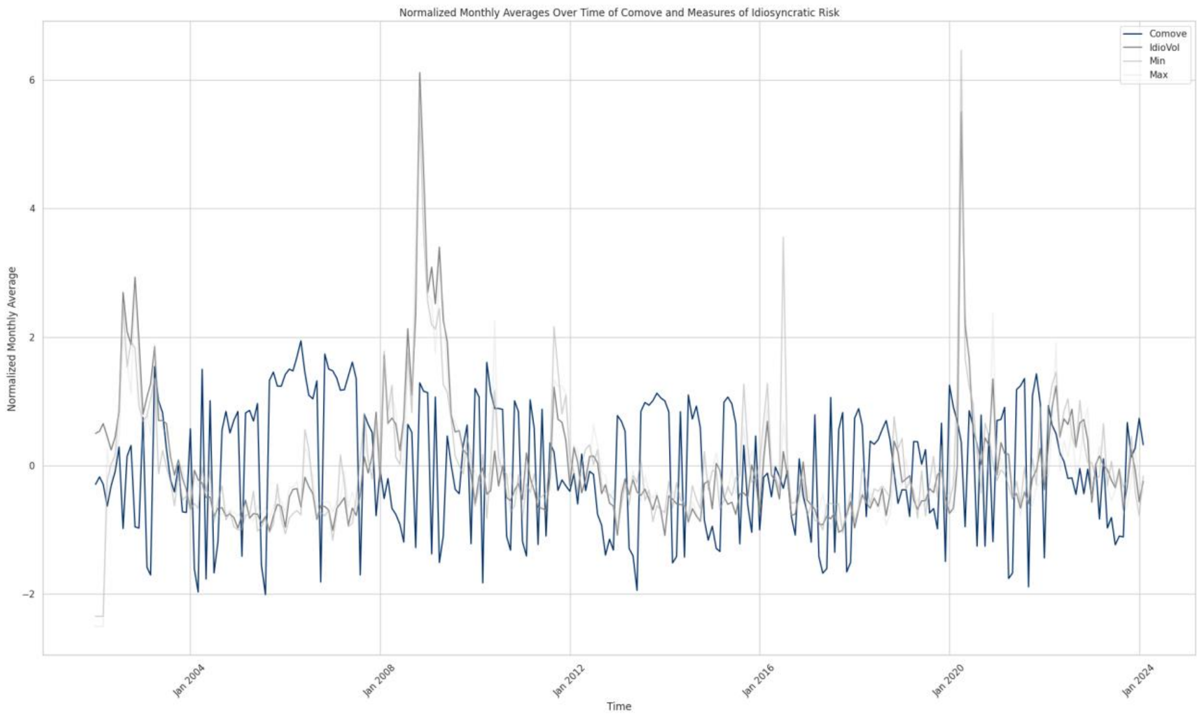

Figure 11 - Normalized Monthly Averages Over Time of Comove and Measures of Idiosyncratic Risk.

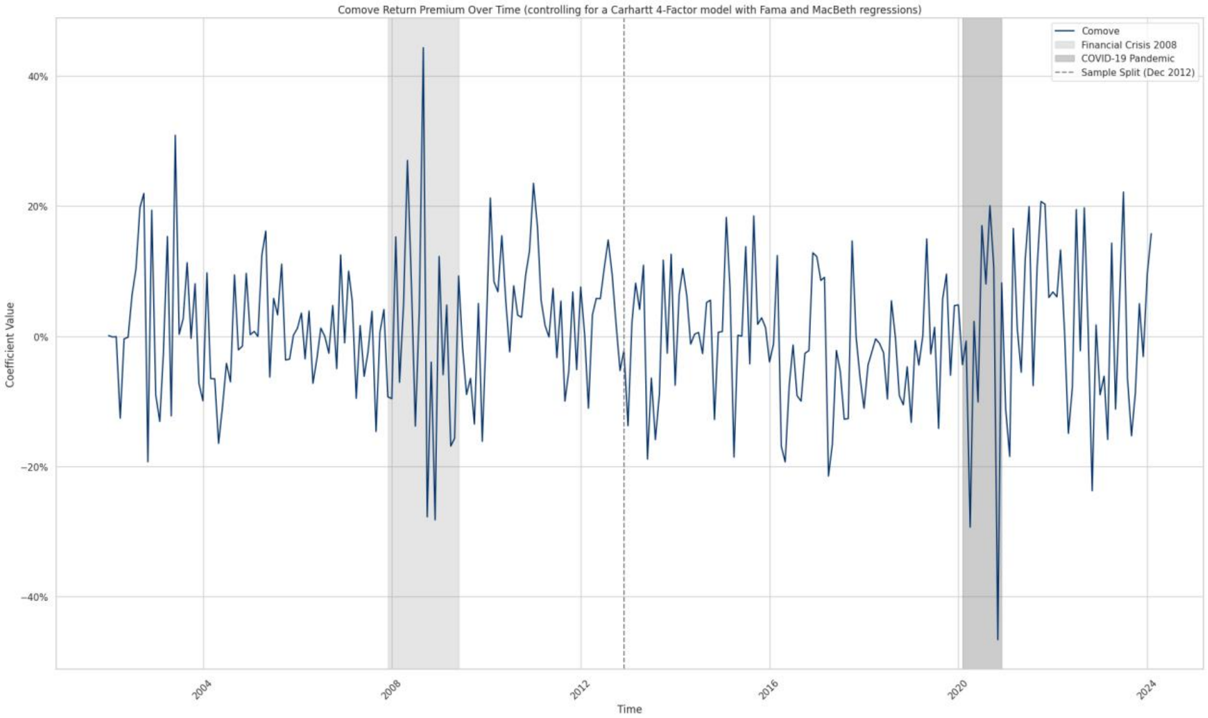

Figure 12 - Comove Return Premium Over Time, after controlling for a Carhart's (1997) four factors with Fama and MacBeth regressions.

*Figure 13 - Google Searches for the search term "Risk" worldwide in the category exchanges and financial support (*Google Searches for the Search Term 'Risk'*, 2024).*

8 Additional Tables

Table 3 - Summary of Main Results

Panel A: Sort by Comove, Controlling for Beta

	Jan 2002 - Feb 2024		Jan 2002 - Dec 2012		Jan 2013 - Feb 2024	
	Raw	*Carhart Alpha*	*Raw*	*Carhart Alpha*	*Raw*	*Carhart Alpha*
Low comove	0.2764%	0.1603%	0.0755%	-0.0393%	0.4743%	0.3401%
2	0.5727%	0.4396%	0.4471%	0.3381%	0.6963%	0.4579%
3	0.5961%	0.4449%	0.5456%	0.4725%	0.6458%	0.2880%
4	0.7252%	0.6208%	0.7090%	0.6635%	0.7412%	0.4361%
High comove	0.7809%	0.6113%	0.7029%	0.6311%	0.8577%	0.3984%
High-Low	0.5045%	0.4510%	0.6274%	0.6704%	0.3834%	0.0582%
Significance		*		*		
Annualized	6.0539%	5.4119%	7.5292%	8.0443%	4.6007%	0.6986%
P-value	0.1441	0.0904	0.2088	0.0849	0.4224	0.8493

Panel B: High-Low Strategy, Other Factor Models

	Jan 2002 - Feb 2024		Jan 2002 - Dec 2012		Jan 2013 - Feb 2024		Available
	Alpha	*Annualized Alpha*	*Alpha*	*Annualized Alpha*	*Alpha*	*Annualized Alpha*	
Raw	0.5045%	6.0539%	0.6274%	7.5292%	0.3834%	4.6007%	Jan 2002 - Feb 2024
CAPM	0.5638%	6.7651%	0.6428%	7.7132%	0.5052%	6.0619%	Jan 2002 - Feb 2024
	***		**		*		
3F	0.6226%	7.4717%	0.7524%	9.0291%	0.5038%	6.0461%	Jan 2002 - Feb 2024
	***		***		**		
4F	0.4510%	5.4119%	0.6704%	8.0443%	0.0582%	0.6986%	Jan 2002 - Feb 2024
	*		*				
4F + QMJ	0.7085%	8.5024%	1.0388%	12.4651%	0.0888%	1.0656%	Jan 2002 - Feb 2024
	**		***				
4F + BAB	0.4518%	5.4214%	0.6833%	8.1992%	0.0581%	0.6977%	Jan 2002 - Dec 2016
	*		*				
4F + Carry	0.5725%	6.8702%	0.7825%	9.3899%	-0.1730%	-2.0758%	Jan 2002 - Dec 2016
	*		**				
4F + Seasonality	0.6451%	7.7416%	0.8425%	10.1095%	0.3054%	3.6650%	Jan 2002 - Dec 2016
	**		**				
5F	0.8821%	10.5857%	1.0597%	12.7163%	0.6505%	7.8064%	Jan 2002 - Feb 2024
	***		***		***		

Table 4 - Summary of Robustness Results with Alternative Factor Measures

Alternative Factor Measures							
	Jan 2002 - Feb 2024		**Jan 2002 - Dec 2012**		**Jan 2013 - Feb 2024**		**Available**
	Alpha	*Annualized Alpha*	*Alpha*	*Annualized Alpha*	*Alpha*	*Annualized Alpha*	
4F with estimated market premium	0.4873%	5.8481%	0.7201%	8.6416%	0.1743%	2.0911%	Jan 2002 - Feb 2024
	**		**				
4F with HML_Devil	0.7492%	8.9905%	0.9826%	11.7915%	0.3377%	4.0529%	Jan 2002 - Feb 2024
	**		***				
4F + UMD_Trend	0.5752%	6.9026%	0.6699%	8.0392%	0.3029%	3.6352%	Jan 2002 - Dec 2016
	*		*				

Table 5 - Summary of Robustness Results with Alternative Index

Alternative Index: (Annualized) Alpha across Different Regions						
	AMX	**BEL20**	**CAC40**	**DAX**	**OMX**	**SMI**
Raw	-0.5900% (-7.0800%)	0.1300% (1.5600%)	0.2400% (2.8800%)	0.3900% (4.6800%)	0.7300% (8.7600%)	0.2400% (2.8800%)
CAPM	-0.6621% (-7.9458%)	0.1132% (1.3581%)	0.3197% (3.8368%)	0.5997% (7.1961%)	0.4251% (5.1017%)	0.3311% (3.9730%)
3F	-0.5663% (-6.7958%)	0.1542% (1.8508%)	0.3667% (4.4009%)	0.5463% (6.5555%)	0.4506% (5.4076%)	0.3984% (4.7807%)
4F	-0.5425% (-6.5100%)	-0.0591% (-0.7096%)	0.3025% (3.6297%)	0.1322% (1.5864%)	-0.1796% (-2.1551%)	0.3154% (3.7848%)
5F	0.0201% (0.2415%)	0.0274% (0.3287%)	0.5758% (6.9099%) **	0.3004% (3.6042%)	0.4656% (5.5870%)	0.4678% (5.6141%)
Region	Netherlands	Belgium	France	Germany	Sweden	Switzerland
ISIN Code	NL0000000107	BE0389555039	FR0003500008	DE0008469008	SE0000337842	CH0009980894
Period Analyzed	April 2002 Dec 2002	July 2002 Dec 2002	July 2000 Dec 2002	July 2000 Dec 2002	July 2004 Dec 2002	July 2001 Dec 2002
Monthly N	25	20	40	40	30	20

Table 6 - Summary of Robustness Results with Alternative Portfolio Aggregation

Robustness Results: Alternative Portfolio Aggregation		
Panel A: Sort by Comove, Controlling for Beta		
	Jan 2002 - Feb 2024	
	Raw	*Carhart Alpha*
Low comove	0.3532%	0.2852%
2	0.6169%	0.5546%
3	0.6953%	0.6587%
4	0.8135%	0.7866%
High comove	0.9305%	0.7364%
High-Low	0.5773%	0.4511%
Significance		*
Annualized	6.9276%	5.4135%
P-value	0.06782	0.0847

Panel B: High-Low Strategy, Other Factor Models			
	Jan 2002 - Feb 2024		**Available**
	Alpha	*Annualized Alpha*	
Raw	0.5800%	6.9600%	Jan 2002 - Feb 2024
	*		
CAPM	0.6330%	7.5962%	Jan 2002 - Feb 2024
	***		
3F	0.6796%	8.1546%	Jan 2002 - Feb 2024
	***		
4F	0.4511%	5.4135%	Jan 2002 - Feb 2024
	*		
4F + QMJ	0.7142%	8.5709%	Jan 2002 - Feb 2024
	***		
4F + BAB	0.4630%	5.5554%	Jan 2002 - Dec 2016
	*		
4F + Carry	0.5073%	6.0880%	Jan 2002 - Dec 2016
4F + Seasonality	0.0056%	0.0678%	Jan 2002 - Dec 2016
	*		
5F	0.9246%	11.0951%	Jan 2002 - Feb 2024
	***		

Table 7 - Univariate Distributions of the Main Variables used in Robustness Tests with Fama and MacBeth Regressions.

Robustness Tests: Fama and MacBeth Regressions						
Univariate Distribution of Main Variables						
	Mean	**Median**	**Standard Deviation**	**10th Percentile**	**90th Percentile**	**N**
Comove	0.5165	0.5192	0.0936	0.3962	0.6346	159606
Return	0.0066	0.0073	0.0940	-0.0951	0.1056	159579
Size	15.7772	15.6355	1.1286	14.4254	17.3819	157586
Value	7.7173	7.6683	0.8034	6.7882	8.7255	147372
Momentum	0.1112	0.0919	0.3689	-0.2909	0.4970	158016
Beta	0.9915	0.9635	0.4084	0.4950	1.5172	159571
Upside Beta	0.5550	0.5278	0.3029	0.1951	0.9447	159569
Downside Beta	0.5313	0.4914	0.3514	0.1548	0.9631	159568
Lower Tail Dependence	0.5402	0.5752	0.1780	0.2838	0.7398	159606
Upper Tail Dependence	0.4570	0.4687	0.1322	0.2780	0.6195	159571
Idiosyncratic Volatility	1.4639	1.2424	0.9290	0.7126	2.4125	159529
Min.	0.0367	0.0297	0.0294	0.0141	0.0650	159574
Max.	0.0396	0.0321	0.0304	0.0164	0.0699	159574

Table 8 - Summary of Robustness Results with Fama and MacBeth Regressions and Other Measurements of Dependence and Volatility.

Robustness Tests: Fama and MacBeth Regressions							
Other Measurements of Dependence and Volatility							
	4F Baseline	**Asymmetric Risk (1)**	**Asymmetric Risk (2)**	**Idiosyncratic Risk (1)**	**Idiosyncratic Risk (2)**	**Illiquidity**	**Trading Activity**
	Coefficient (Annual)	*Coefficient (Annual)*	*Coefficient (Annual)*	*Coefficient (Annual)*	*Coefficient (Annual)*	*Coefficient (Annual)*	*Coefficient (Annual)*
Comove	0.0059 (7.0727%) ***	0.0072 (8.6414%) ***	0.0062 (7.4512%) ***	0.0058 (7.0072%) ***	0.0046 (5.5717%) **	0.0001 (0.1005%) ***	0.0059 (7.1019%) ***
Beta	-0.0026 (-3.0930%) ***	0.0027 (3.2133%) *	-0.0020 (-2.3528%) **	-0.0020 (-2.4476%) ***	-0.0015 (-1.8087%) ***	0.0000 (-0.0321%) ***	-0.0025 (-3.0345%) ***
Size	0.0015 (1.7748%) ***	0.0017 (2.0090%) ***	0.0017 (2.0983%) ***	0.0014 (1.6295%) ***	0.0014 (1.7260%) ***	0.0000 (0.0218%) ***	0.0014 (1.7175%) ***
Value	-0.0006 (-0.7531%) **	-0.0001 (-0.0745%) **	-0.0007 (-0.8019%) **	-0.0006 (-0.6643%) **	-0.0006 (-0.7371%) **	-0.0004 (-0.4751%)	-0.0008 (-0.9656%) ***
Momentum	0.0069 (8.3182%) ***	0.0070 (8.4002%) ***	0.0075 (8.9596%) ***	0.0075 (9.0537%) ***	0.0073 (8.8187%) ***	0.0061 (7.3771%) ***	0.0073 (8.7529%) ***
Upside Beta		-0.0029 (-3.5079%) *					
Downside Beta		-0.0032 (-3.8488%) ***					
UTD			-0.0444 (-53.3207%) ***				
LTD			0.0332 (39.8770%) ***				
IdioVol				-0.0013 (-1.5819%) ***			
Min					-0.0025 (-30.5795%) *		
Max					-1.8389 (-2206.6299%)		
Illiquidity						482.2427 (578,691.2954%) ***	
Ln(Turnover)							-0.0001 (-0.0721%) ***
Diff in Ln(Turnover)							0.0008 (0.9787%) ***
Avg. R^2	11.40%	12.71%	12.56%	12.49%	12.83%	12.15%	12.33%
Avg. N	548	548	548	548	548	488	548
T	266	266	266	266	266	266	266

Table 9 - Summary of Robustness Results with Fama and MacBeth Regressions and Other Benchmarks, Fixed Effects and Comove with a Skipped Month.

Robustness Tests: Fama and MacBeth Regressions Other Benchmarks, Fixed Effects and Comove with a Skipped Month.				
	4F with Different Momentums	**5F**	**Fixed Effects**	**Comove with Skipped Month**
	Coefficient (Annual)	*Coefficient (Annual)*	*Coefficient (Annual)*	*Coefficient (Annual)*
Comove	0.0007 (0.8608%)	0.0153 (18.3706%) ***	0.0027 (3.1951%)	
Comove with Skipped Month				0.0001 (0.0649%) ***
Beta	-0.0015 (-1.8152%) ***	-0.0008 (-0.9471% %)	-0.0031 (-3.6734%) ***	-0.026 (-3.071%) ***
Size	0.0013 (1.5844%) ***	0.0021 (2.5435%) ***	0.0028 (3.3143%) ***	-0.0015 (1.7826%) ***
Value	-0.0007 (-0.8852%) **	-0.0006 (-0.6857%) **	-0.0013 (-1.5096%) ***	-0.0006 (-0.7183%) **
Momentum			0.0035 (4.1426%) ***	0.0050 (6.0171%) ***
Short-Term Momentum	-0.0174 (-20.8995%) ***			
Medium-Term Momentum	0.0031 (3.7153%) ***			
Long-Term Momentum	0.0019 (2.2781%) ***			
Profitability		0.0000 (0.0000%) ***		
Investment		0.0065 (7.7660%) ***		
Fixed Effects			Various	
Avg. R^2	13.59%	11.01%	48.52%	11.35%
Avg. N	538	545	548	548
T	229	266	266	266

Table 10 -Summary of Robustness Results with Fama and MacBeth Regressions while varying the Comove measure and the sample.

Robustness Tests: Fama and MacBeth Regressions						
Varying the Comove Measure and the Sample.						
	4F with Comove Monthly	**4F with Comove Daily**	**4F with EUR50**	**4F excluding small size, small price, and LN**	**4F with Sample Split: Jan 2002 – Dec 2012**	**4F with Sample Split: Jan 2013 – Feb 2023**
	Coefficient (Annual)	*Coefficient (Annual)*	*Coefficient (Annual)*	*Coefficient (Annual)*	*Coefficient (Annual)*	*Coefficient (Annual)*
Comove				0.0059 (7,0727%) ***	0,0148 (17,7417%) ***	-0.0029 (-3.4371%)
Comove Monthly	0.0000 (-0.0498%) *					
Comove Daily		0.0000 (0.0213%)				
Comove EUR50			0.0001 (0.0833%) ***			
Beta	-0.0026 (-3.1740%) ***	-0.0024 (-2.9325%) ***	-0.0026 (-3.0930%) ***	-0.0026 (-3.0930%)	-0.0046 (-5.5344%) ***	-0.0006 (-0.6880%)
Size	0.0015 (1.8271%) ***	0.0016 (1.9460%) ***	0.0015 (1.7748%) ***	0.0015 (1.7748%) ***	0.0010 (1.2229%) ***	0.0019 (2.3185%) ***
Value	-0.0007 (-0.8023%) **	-0.0007 (-0.8249%) **	-0.0006 (-0.7531%) **	-0.0006 (-0.7531%) **	-0.0011 (-1.3514%) **	-0.0001 (-0.1637%)
Momentum	0.0055 (6.5578%) ***	0.0063 (7.5102%) ***	0.0069 (8.3182%) ***	0.0069 (8.3182%) ***	0.0031 (3.6823%) ***	0.0107 (12.8848%) ***
Avg. R^2	11.46%	11.61%	11.40%	11.40%	11.40%	11.41%
Avg. N	547	548	548	548	515	581
T	266	266	266	266	132	134

9 Appendix

9.1 Appendix A: Overview of Variables in Equity Pricing Factor Models

In the analysis, various factor models were employed. The utilization and meaning of data in the original study by Ungeheuer and Weber (2020), as well as in this research paper, are delineated in the tables below. An asterisk in the table indicates that, although the factor was not initially suggested within a factor model's framework, it was nonetheless examined within the context of this model during the analysis of this paper.

Table 11 - Overview of Equity Pricing Factors: Data definitions and sources.

Panel A: Market Premium				
Prevalence in models	**CAPM** *(Sharpe, 1964)*	**3-Factor Model** *(Fama & French, 1993)*	**4-Factor Model** *(Carhart, 1997)*	**5-Factor Model** *(Fama & French, 2015)*
	X	X	X	X
Meaning	The expected return on the market minus the risk-free rate. In literature, this is often quantified by taking the difference between the return on a broad market index and a proxy for the risk-free rate.			
Original Paper	Sharpe (1964) introduced the market premium in his Capital Asset Pricing Model.			
Data	In the paper about the American stock market (Ungeheuer & Weber, 2020): Monthly American value-weighted market return minus the one-month Treasury bill rate, according to Kenneth French's data library (French, 2024a).			
	Main tests of thesis: Similar to the work of Ungeheuer & Weber (2020), the monthly European 5-Factor dataset of Kenneth French's data library was used (French, 2024b).			
	Robustness tests of thesis: Using the calculated monthly market return of the EUR600 index, minus the risk-free rate in Europe. The risk-free rate can be proxied by the EONIA (Euro Overnight Index Average) rates for the months up to October 2019. From October 2019 onwards, the €STR (Euro Short-Term Rate) becomes the relevant benchmark. All return indexes are retrieved from DataStream software.			

Panel B: Size (Small-Minus-Big)				
Prevalence in models	**CAPM** *(Sharpe, 1964)*	**3-Factor Model** *(Fama & French, 1993)*	**4-Factor Model** *(Carhart, 1997)*	**5-Factor Model** *(Fama & French, 2015)*
		X	X	X
Meaning	Smaller companies (by market capitalization) tend to have higher returns than larger companies. In literature, market capitalization data is used to sort firms into size portfolios.			
Original Paper	Fama and French (1993) introduced the SMB factor in their 3-Factor model.			
Data	In the paper about the American stock market (Ungeheuer & Weber, 2020): The average return on the nine American small stock portfolios minus the average return on the nine American big stock portfolios, according to Kenneth French's data library (French, 2024a).			
	Main tests of thesis: Similar to the work of Ungeheur & Weber (2020), the monthly European 5-Factor dataset of Kenneth French's data library was used (French, 2024b).			

Panel C: Value (High-Minus-Low)				
Prevalence in models	**CAPM** *(Sharpe, 1964)*	**3-Factor Model** *(Fama & French, 1993)*	**4-Factor Model** *(Carhart, 1997)*	**5-Factor Model** *(Fama & French, 2015)*
		X	X	X
Meaning	Companies with high book-to-market ratios (value companies) tend to outperform those with low book-to-market ratios (growth companies). In literature, book-to-market ratios are used to sort firms into value and growth portfolios.			

Original Paper	Fama and French (1993) introduced the HML factor in their 3-Factor model.			
Data	In the paper about the American stock market (Ungeheuer & Weber, 2020): The average return on the two American value portfolios minus the average return on the two American growth portfolios, according to Kenneth French's data library (French, 2024c).			
	Main tests of thesis: Similar to the work of Ungeheur & Weber (2020), the monthly European 5-Factor dataset of Kenneth French's data library was used (French, 2024b).			
	Robustness test of thesis: Using the monthly European HML Devil factor of the AQR database (AQR Capital Management, 2024a), which is based on the work of Asness and Frazzini (2011) in their paper "The devil in HML's Details". They argue that the traditional HML factor, as formulated by Fama and French, may not fully capture the essence of the value premium because it relies solely on book-to-market ratios without considering the quality or profitability of the underlying companies. They propose an alternative measurement, which is referred to as HML_Devil in this thesis.			

Panel D: Momentum (Up-Minus-Down)

Prevalence in models	**CAPM** *(Sharpe, 1964)*	**3-Factor Model** *(Fama & French, 1993)*	**4-Factor Model** *(Carhart, 1997)*	**5-Factor Model** *(Fama & French, 2015)*
			X	
Meaning	Stocks that have performed well in the past ("winners") tend to continue performing well in the near future, and vice versa. In literature, past returns (usually over the past 3 to 12 months, excluding the most recent month) are used to sort firms into winning and losing portfolios.			
Original Paper	Carhart (1997) introduced the UMD factor in his 4-Factor model.			
Data	In the paper about the American stock market (Ungeheuer & Weber, 2020): The average return on the two American high prior return portfolios minus the average return on the two American low prior return portfolios, according to Kenneth French's data library (French, 2024c).			
	Main tests of thesis: Using the monthly European UMD factor of the AQR database (AQR Capital Management, 2024a), which uses the returns of the past twelve months (skipping the most recent month).			
	Robustness test of thesis: Using the monthly global equity trend factor in the dataset of the Erasmus University Rotterdam (Baltussen et al., 2021), which is made for the work of Baltussen, Swinkels and Van Vliet (2019). Their calculations are based on a paper of Moskowit, Ooi and Pedersen (2011), in which the trend factor was originally introduced. The trend factor capitalizes on the momentum effect over longer periods. It suggests that assets that have exhibited a strong performance trend over the past several months to years tend to continue performing well. Note that the trend factor serves as an additional factor, and not as a replacement for the momentum factor (UMD).			

Panel E: Profitability (Robust-Minus-Weak)

Prevalence in models	**CAPM** *(Sharpe, 1964)*	**3-Factor Model** *(Fama & French, 1993)*	**4-Factor Model** *(Carhart, 1997)*	**5-Factor Model** *(Fama & French, 2015)*
				X
Meaning	Companies with higher profitability tend to have higher returns. In literature, profitability measures such as return on equity or return on assets are used to sort firms into portfolios.			
Original Paper	Fama and French (2015) introduced the RMW factor in their 5-Factor model.			
Data	In the paper about the American stock market (Ungeheuer & Weber, 2020): The average return on the two American robust operating profitability portfolios minus the average return on the two American weak operating profitability portfolios, according to Kenneth French's data library (French, 2024a).			
	Main tests of thesis: Similar to the work of Ungeheur & Weber (2020), the monthly European 5-Factor dataset of Kenneth French's data library was used (French, 2024b).			

Panel F: Investment (Conservative-Minus-Aggressive)

Prevalence in models	**CAPM** *(Sharpe, 1964)*	**3-Factor Model** *(Fama & French, 1993)*	**4-Factor Model** *(Carhart, 1997)*	**5-Factor Model** *(Fama & French, 2015)*
				X
Meaning	Companies with lower investment rates tend to have higher returns. In literature, investment-to-assets ratios or growth in total assets are used to sort firms into portfolios.			

Original Paper	Fama and French (2015) introduced the CMA factor in their 5-Factor model.			
Data	In the paper about the American stock market (Ungeheuer & Weber, 2020): The average return on the two American conservative investment portfolios minus the average return on the two American aggressive investment portfolios, according to Kenneth French's data library (French, 2024a). Main tests of thesis: Similar to the work of Ungeheur & Weber (2020), the monthly European 5-Factor dataset of Kenneth French's data library was used (French, 2024b).			
Panel G: Betting-Against-Beta				
Prevalence in models	**CAPM** *(Sharpe, 1964)*	**3-Factor Model** *(Fama & French, 1993)*	**4-Factor Model** *(Carhart, 1997)*	**5-Factor Model** *(Fama & French, 2015)*
			*X**	
Meaning	Securities with lower beta tend to generate higher adjusted returns than predicted by CAPM. In literature, beta is calculated relative to a market index.			
Original Paper	Frazzini and Pedersen (2014) introduce the BAB factor as a test or special case of the CAPM.			
Data	In the paper about the American stock market (Ungeheuer & Weber, 2020): Betting-against-beta factor returns according to Frazzini and Pedersen (2014). It is tested as an extension to the Carhart's 4F model. Main tests of thesis: Using the monthly European BAB factor of AQR database (AQR Capital Management, 2024a), which is based on the work of Frazzini and Pederson (2014). It is tested as an extension to the Carhart's 4F model.			
Panel H: Financial Health (Quality-Minus-Junk)				
Prevalence in models	**CAPM** *(Sharpe, 1964)*	**3-Factor Model** *(Fama & French, 1993)*	**4-Factor Model** *(Carhart, 1997)*	**5-Factor Model** *(Fama & French, 2015)*
			*X**	
Meaning	High-quality stocks (measured by profitability, growth, safety, etc.) tend to outperform low-quality stocks. In literature, various metrics of financial health and stability are used to classify stocks into quality and junk.			
Original Paper	In the work of Asness, Frazzini, and Pedersen (2017), the QMJ factor is proposed and tested in combination to different other factors such as size, value, momentum, investments, profitability and betting against beta.			
Data	In the paper about the American stock market (Ungeheuer & Weber, 2020): Asness et al. (2017) quality-minus-junk factor returns. It is tested as an extension to the Carhart's 4F model. Main tests of thesis: Using the monthly European QMJ factor of the AQR Database (AQR Capital Management, 2024b), which is based on the working version of the paper of Asness et al. (2017). It is tested as an extension to the Carhart's 4F model.			
Panel I: Carry				
Prevalence in models	**CAPM** *(Sharpe, 1964)*	**3-Factor Model** *(Fama & French, 1993)*	**4-Factor Model** *(Carhart, 1997)*	**5-Factor Model** *(Fama & French, 2015)*
			*X**	
Meaning	The carry factor refers to the return obtained from holding and rolling over leveraged positions in currency, commodities, or securities markets, usually exploiting differences in interest rates or yield curves.			
Original Paper	The concept of "carry" as a factor in finance does not originate from a single paper but rather evolved through practical application. The formalization of carry as a systematic risk factor across multiple asset classes has been done by Koijen et al. (2016).			
Data	In the paper about the American stock market (Ungeheuer & Weber, 2020): Not tested. Main tests of thesis: Using the monthly global carry factor in the dataset of the Erasmus University Rotterdam (Baltussen et al., 2021), which is made for the work of Baltussen, Swinkels and Van Vliet (2019). Their calculations are based on a paper of Koijen et al. (2016).			
Panel J: Seasonal				
Prevalence in models	**CAPM** *(Sharpe, 1964)*	**3-Factor Model** *(Fama & French, 1993)*	**4-Factor Model** *(Carhart, 1997)*	**5-Factor Model** *(Fama & French, 2015)*

			X*	
Meaning	Seasonality refers to predictable changes in asset returns at certain times of the year, month, or even week. This can be due to various factors, including fiscal policies, holiday effects, or agricultural cycles.			
Original Paper	Keloharju, Linnainmaa, and Nyberg (2016) discover a small return seasonality premium.			
Data	In the paper about the American stock market (Ungeheuer & Weber, 2020): Not tested.			
	Main tests of thesis: Using the monthly global seasonal factor in the dataset of the Erasmus University Rotterdam (Baltussen et al., 2021), which is made for the work of Baltussen, Swinkels and Van Vliet (2019). Their calculations are based on a paper of Keloharju, Linnainmaa, and Nyberg (2016).			

This thesis also references additional factors; however, challenges were encountered in testing these due to the unavailability of European data or other testing complications.

- The tail risk factor (Kelly & Jiang, 2014), which is tested in the work of Weber & Ungeheuer.
- The liquidity factor (Pastor & Stambaugh, 2001), which is tested in the work of Weber & Ungeheuer.
- The systematic liquidity factors (Sadka, 2003), which is tested in the work of Weber & Ungeheuer.
- The undervalued-minus-overvalued factor (Hirshleifer & Jiang, 2010), which is tested in the work of Weber & Ungeheuer.
- The mispricing factors (Stambaugh & Yuan, 2016), which is tested in the work of Weber & Ungeheuer.
- The Arbitrage Pricing Theory (Ross, 1976) is a multi-factor model that suggests that assets returns can be modeled as a linear function of numerous factor variables, but not specify particular risk factors to test.
- Macro-factor and global factor models such as the one of Chen e. a. (1986) are considered out of scope to test.
- Multi-period models such as the one of Merton (1973) are considered out of scope to test.
- Behavioral models, such as the one of Baker & Wurgler (2006), are considered out of scope to test.

9.2 Appendix B: Overview of Variables in Fama & MacBeth Regressions

The subsequent section provides an overview of the variables utilized in the Fama and MacBeth regression analyses conducted as part of the robustness tests. All requisite data are denominated in euros and sourced from DataStream. The first column presents the complete names and symbols of the variables, while the subsequent columns detail the necessary data and the calculations performed using this data. The return for a given period is calculated as the percentage difference in the return index between the last weekday prior to the start of the period and the last weekday within the period itself. The index refers to the EUR600.

Table 12 - Main variables used in Fama and MacBeth Regressions, illustrated for the month January.

Time Intervals for Variables of Individual Stocks: Main Variables													
	20XX - 1												**20XX**
	Jan	*Feb*	*March*	*April*	*May*	*June*	*July*	*Aug*	*Sep*	*Oct*	*Nov*	*Dec*	*Jan*
Stocks in the index on ...													**Index**
Main Variables of an Individual Stock													
Comove *comove*	Weekly Returns of Stock and Index *Taking the percentage of weeks that have returns with the same sign, as in Ungeheuer and Weber (2020).*												
Beta *β*	Daily Returns of Stock and Index *Calculating Correlation, as in Ungeheuer and Weber (2020).*												
Return R_t													Daily Return of Stock *Percentual Difference*
Size *ln (marketCap)*	Monthly Market Capitalization of Stock *Taking the natural logarithm of the average, as in Ungeheuer and Weber (2020).*												
Value *ln (BTM)*	Monthly Market Value in Euro of Stock Monthly Common Equity in Euro of Stock *Taking the natural logarithm of the average of the monthly Book-To-Market ratios, as in Ungeheuer and Weber (2020).*												
Momentum $R_{t-12,\, t-2}$	Return of Stock *Percentual Difference, as in Ungeheuer and Weber (2020).*												

Table 13 - Other measurements of dependency and volatility used in Fama and MacBeth Regressions, illustrated for the month January.

Time Intervals for Variables of Individual Stocks: Other Measurements of Dependency and Volatility													
	20XX - 1												**20XX**
	Jan	*Feb*	*March*	*April*	*May*	*June*	*July*	*Aug*	*Sep*	*Oct*	*Nov*	*Dec*	*Jan*
Stocks in the index on …													**Index**
Panel A: Measurements of Downside and Upside Risk of an Individual Stock													
Downside beta *β^-*	Daily Returns of Stock and Index *Calculating correlation of returns in days where the stock return is below the mean index return, as in Chen et al. (1986).*												
Upside Beta *β^+*	Daily Returns of Stock and Index *Calculating correlation of returns in days where the stock return is above the mean index return, as in Chen et al. (1986).*												
Lower tail dependence *LTD*	Daily Returns of Stock and Index *Calculating the lower tail dependence coefficient of the estimated Clayton copula (1978) of the returns with Kendall's tau (1938), based on Chabi-Yo et al. (2017).*												
Upper tail dependence *UTD*	Daily Returns of Stock and Index *Calculating the upper tail dependence coefficient of the estimated Gumbel copula (2019) derived of the return with Kendall's tau (1938), based on Chabi-Yo et al. (2017).*												
Panel B: Measurements of Idiosyncratic Risk of an Individual Stock													
Idiosyncratic Volatility *Idio. Vol.*												Daily Returns Stock and Index *Standard deviation of residuals in the regression $R_{stock,\,t} = \alpha + \beta * R_{market,\,t} + \epsilon_t$, as in Fama and French (1992).*	
Minimum Return *Min*												Daily Return Stock *Taking the minimum and multiply it by -1, as in Bali et al. (2011).*	
Maximum Return *Max*												Daily Return Stock *Taking the maximum, as in Bali et al. (2011).*	
Panel C: Measurements of Illiquidity of an Individual Stock													
Illiquidity Ratio *Amihud*	Daily Return of Stock Daily Trading Volume (by Value) of Stock *Average of the daily Amihud (2002) illiquidity ratio, which is calculated by taking the absolute value of the return and dividing it with the trading volume.*												
Panel D: Measurements of Trading Activity of an Individual Stock													
Turnover *ln (turn)*												Monthly Turnover (by Volume) Stock *Taking the natural logarithm, as in Gervais et al. (2001).*	
Difference in Turnover *Δ ln (turn)*											Monthly Turnover (by Volume) Stock *Calculating the absolute difference in the natural logarithm of both, as in Gervais et al. (2001).*		

Table 14 - Other benchmarks, fixed effects and adjusted comove with skipped month as used in Fama and MacBeth Regressions, illustrated for the month January.

<table>
<tr><th colspan="16">Time Intervals for Variables of Individual Stocks: Other Benchmarks, Fixed Effects and Skipped Month</th></tr>
<tr><th rowspan="2"></th><th rowspan="2">20XX - 3</th><th rowspan="2">20XX - 2</th><th colspan="12">20XX - 1</th><th>20XX</th></tr>
<tr><td>Jan</td><td>Feb</td><td>Mar</td><td>April</td><td>May</td><td>June</td><td>July</td><td>Aug</td><td>Sep</td><td>Oct</td><td>Nov</td><td>Dec</td><td>Jan</td></tr>
<tr><td>Stocks in the index on …</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>Index</td></tr>
<tr><th colspan="16">Panel A: Other benchmarks of an Individual Stock</th></tr>
<tr><td>Short-term momentum
$R_{t-1, t-1}$</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>Daily Return of Stock
Percentual Difference</td><td></td></tr>
<tr><td>Medium-term momentum
$R_{t-12, t-2}$</td><td></td><td></td><td colspan="11">Daily Return of Stock
Percentual Difference</td><td></td><td></td></tr>
<tr><td>Long-term momentum
$R_{t-36, t-13}$</td><td colspan="2">Monthly Return of Stock
Percentual Difference</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Operating Profitability
Op. Profit.</td><td></td><td></td><td colspan="12">Monthly Operating Income of Stock
Taking the average, based on Fama and French (2015).</td><td></td></tr>
<tr><td>Investment
Asset Growth</td><td></td><td></td><td colspan="12">Monthly Total Asset Growth of Stock
Taking the percentual difference in month prior to this period and the last month of this period, based on Fama and French (2015).</td><td></td></tr>
<tr><th colspan="16">Panel B: Fixed Effects of an Individual Stock</th></tr>
<tr><td>Industry</td><td colspan="15">Sector Name of Stock (as defined by Level 6 of Industry Classification Benchmark)
Making Dummy Variables.</td></tr>
<tr><td>Exchange</td><td colspan="15">Exchange of the Stock (as defined by DataStream exchange code)
Making Dummy Variables.</td></tr>
<tr><td>Size</td><td></td><td></td><td colspan="12">Monthly Market Capitalization of Stock
Taking the average and dividing all stocks of this month in deciles.</td><td></td></tr>
<tr><th colspan="16">Panel C: Comovement with Skipped Month of an Individual Stock</th></tr>
<tr><td>Comove with adjusted period</td><td></td><td></td><td colspan="11">Weekly Returns of Stock and Index
Taking the percentage of weeks that have returns with the same sign, as in Ungeheuer and Weber (2020).</td><td></td><td></td></tr>
</table>

Table 15 - Variables used when varying the comove measure and the sample in the Fama and MacBeth regressions, illustrated for the month January.

Time Intervals for Variables of Individual Stocks: Varying the Comove Measure and the Sample															
	20XX - 3	**20XX - 2**	**20XX - 1**												**20XX**
			Jan	*Feb*	*Mar*	*April*	*May*	*June*	*July*	*Aug*	*Sep*	*Oct*	*Nov*	*Dec*	*Jan*
Stocks in the index on …															**Index**
Panel A: Varying the Comove Measure															
Comove with monthly frequency	Monthly Returns of Stock and Index *Taking the percentage of months that have returns with the same sign, as in Ungeheuer and Weber (2020).*														
Comove with daily frequency			Daily Returns of Stock and Index *Taking the percentage of days that have returns with the same sign, as in Ungeheuer and Weber (2020).*												
Comove with EUR50			Weekly Returns of Stock and EUR50 *Taking the percentage of weeks that have returns with the same sign, as in Ungeheuer and Weber (2020).*												
Panel B: Varying the Sample															
Excluding stocks from Londen Stock Exchange	Industry of the Stock *Exclude when equal to LN.*														
Excluding small stocks	Monthly Market Capitalization of the Stock *Exclude when in the lowest decile compared to other stocks analyzed in this month.*														
Excluding low price stocks	End-of-the-month Return Index of the Stock *Exclude when below 5 euro.*														
Sample split	*Analyze the periods Jan 2002 - Dec 2012 and Jan 2013 - Feb 2024 separately.*														

9.3 Appendix C: Use of Technologies

In the development of my thesis, several technologies have been pivotal in facilitating various aspects of my research.

9.3.1 Data Collection Technologies

DataStream as the Primary Data Source: DataStream was employed as the main source of data for this thesis. Given its nature as a paid service, DataStream provided a reliable and comprehensive dataset. All utilized mnemonics and queries are available on GitHub. An example of a typical query used to extract data from DataStream is:

```
=@Thomson.Reuters.AFOSpreadsheetFormulas.DSGRID("LDJSTOXX0123";"X(R)~EI";"2023-01-01";"2023-12-31";"D";"RowHeader=true;TimeSeriesList=true;ColHeader=true;Heading=true;Curn=true;DispSeriesDescription=true;YearlyTSFormat=false;QuarterlyTSFormat=false;MonthlyTSFormat=False";"")
```

9.3.2 Data Processing Technologies

Jupyter Notebook for Data Analysis: The use of Jupyter Notebook was crucial for data processing and conducting statistical tests. Its interactive environment using code (e.g., Python) and text. All code and text are written by the author of this thesis.

GitHub Repository for Publishing Code: All Jupyter Notebooks related to this project are available on my GitHub repository (https://github.com/lunageens/PerceivedMarketDependence). As the access to DataStream is restricted through a subscription model, data is not included. However, the publication of these notebooks ensures the validity of the research, enabling other researchers to replicate the studies under similar conditions.

9.3.3 AI-Related Technologies

ChatGPT as a Language, Coding and Search Assistant: Throughout my research, ChatGPT has served as a language assistant, aiding in rewriting text; improving code and offering initial search capabilities. Examples of queries are:

Write this in an academdic text, i want it to be a short text where i acknowledge the technologies is used for my thesis:

AI Related: Chat gtp als language assistant and first search robot, examples of promots are: {}. Connected papers as search robot for literature overview.

Data Process Related: Jupyter notebook was used to process the data and carry out the statistical tests. All jupyter notebooks are published on the Github of the author: /// link. The data in this gitHub account is sample data and will not have the same results, since DataStream is a paid data Source. It ensures validaty of research so others can repeat it.

Data Collection Related: DataStream was used as data Source, this is paid. Example of a prompt used is: {}

Knowing that my dataset has an index column MMYYYY that for each month, contains 5 rows raning with Comove rank 1 to 5. how can i display a plot over time? how can i alter this code:

```
# Step 3: Plotting 'Avg. Return' per 'Comove Rank' over time
# Assuming there is a time column named 'Time'
plt.figure(figsize=(10, 6))
for rank in sorted(data['Comove rank'].unique()):
    subset = data[data['Comove rank'] == rank]
    plt.plot(subset['Avg. Return'], label=f'Comove Rank {rank}')
plt.xlabel('Time')
plt.ylabel('Average Return')
plt.title('Average Return per Comove Rank Over Time')
plt.legend()
plt.show()
```

In the following paper there is talked about a factor called HML Devil, and i was wondering it if it is as a replacement for the original value factor (HML) or as an additional factor? Asness, Cliff S. and Frazzini, Andrea, The Devil in HML's Details (September 26, 2011). Available at SSRN: https://ssrn.com/abstract=2054749 or http://dx.doi.org/10.2139/ssrn.2054749

Connected Papers for Literature Overview: To construct a comprehensive literature review, I utilized the website of Connected Papers, a specialized search engine for academic papers. This tool helped in identifying relevant studies and understanding the interconnectedness of various works within my field of study.

10 Declaration On Word of Honour

I hereby declare that I know what plagiarism entails, namely to use another’s work and to present it as my own without attributing the sources in the correct way.

I acknowledge that copying someone else's assignment or essay, or part of it, is wrong, and declare that this is my own work.

I have used the American Psychological Association (APA) as the convention for citation and referencing. Each significant contribution to, and quotation in, this essay/report/project/… from the work, or works of other people has been attributed and has cited and referenced.

This Master’s thesis is my own original work and has not yet been handed in at any other university, nor had it been published.

I am aware of the consequences of fraud as stated in the exam regulation of the University of Antwerp.

Date 21/05/2024

Name Luna Geens

Signature