University of Antwerp
Faculty of Business and Economics

Perceived Market Dependence and its Effect on Stock Returns

An Empirical Analysis of European Markets
Thesis defence to obtain the degree of
Digital Business Engineering

Presented by Luna Geens
Promoted by Prof. dr. Jan Annaert

Contribution to literature and SDGs

1) This thesis contributes to **empirical asset pricing literature** by challenging traditional metrics used to assess market dependency and proposing an alternative approach.

- Sharpe's Beta (194) is criticized for lack of empirical support.
  - *Fama and French (1992): In coherence with earlier evidence, they find that market risk alone is not enough to explain the cross-sections of returns. They propose a three factor model.*
  - *Later evidence also does not support the CAPM. Fama and French (2003) summarize (the lack of) empirical evidence on the CAPM. Celik (2012) reviews all asset pricing models theoretically and emprically.*

- Hypothesis of 'correlation neglect' suggests investors may not fully account for the dependence between individual stock returns and the broader market. This leads to misestimations of market risk.
  - *Enke & Zimmermann (2013): This paper investigates how people often fail to account for correlations in information signals. The study shows that in financial markets, this neglect of correlation can lead to overoptimism and overpessimism, contributing to price bubbles and crashes.*
  - *Eyster & Weizsacker (2016): This study examines correlation neglect in the context of portfolio choices. It finds that participants in laboratory experiments often ignore correlations between asset returns, leading to suboptimal diversification.*

- This thesis, along with recent scholarship, challenges this view: investors do consider dependencies in asset pricing but perceive these dependencies differently than historical correlations suggest.
  - *Bossaerts and Plott (2004): The CAPM's pricing implications hold when market's participant's beliefs about beta are unbiased. They show that individual investors are not close to "the market" but that the aggregate demand is in line with CAPM.*
  - *Laudenbach et al. (2019): Better information presentation (e.g., a realistic sample format instead of descriptions of return distributions) can alleviate correlation neglect.*
  - *Ungeheuer and Weber (2020): People fail to understand dependence in extreme returns and therefore misprice stocks.*

Contribution to literature and SDGs

By introducing an alternative metric:

- Enriches academic discourse on market dependency.

- Enhances the predictive accuracy of asset pricing models in capturing return premia overlooked by beta.

- Contribution to behavioral finance literature: Challenges the notion of mean-variance investors.
  - *As assumed in the Capital Asset Pricing Model (Sharpe, 1964).*
  - *As pioneered in the Modern Portfolio Theory (Markowitz, 1952).*

Contribution to literature and SDGs

2) Empirical findings **extend the work of Ungeheuer and Weber** (2020):

Proposed the frequency of comovement as a more accurate indicator of perceived dependence in North American markets.

- *This approach underweights extreme returns compared to correlation.*
- *Supported by neuroscience suggesting humans struggle to detect and adapt to extreme outcomes (Bossaerts & Plott, 2004).*

Provides robust evidence supporting Ungeheuer and Weber's hypothesis within the European stock market:

- *Empirical validation in a different market setting corroborates previous findings.*
- *Enhances applicability in global asset pricing models.*

3) Additional contributions to **broader asset pricing literature and offers practical insights for portfolio management.**

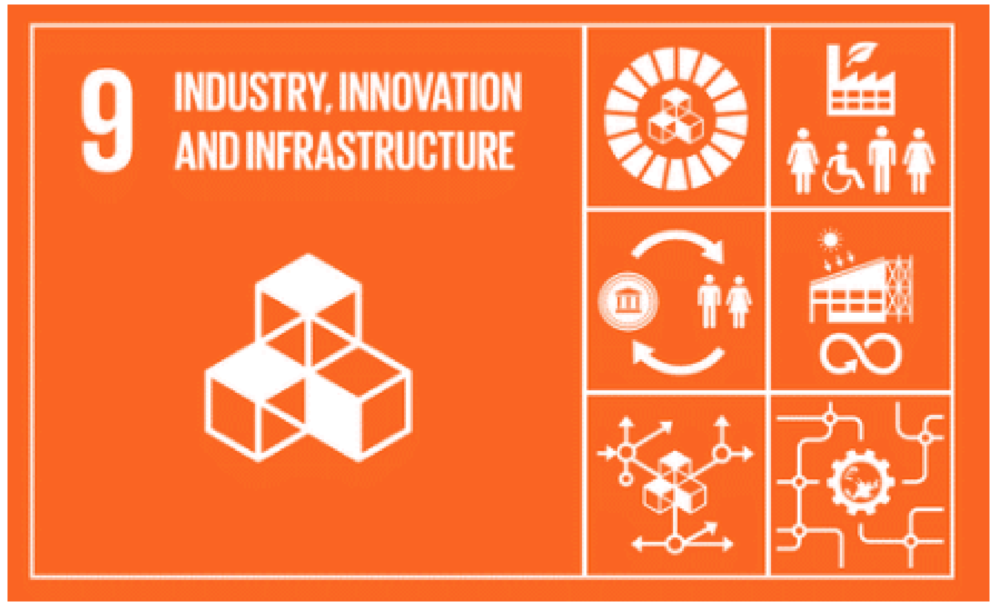
Explores comovement premium across different time periods.

- *Analysis of two periods (January 2002 to December 2012 and January 2013 to February 2024) reveals a decline of the comove return premium in the latter period.*
- *Highlights the dynamic nature of the comovement premium over time.*
- *Partly contradicts Ungeheuer and Weber (2020)*
- *Aligns with other studies showing beta varies over time (Blume, 1971, 1975; Ferson & Harvey, 1991; Jagannathan & Wang, 1996).*

Examines the impact of various risk factors on the comovement premium:

- *Includes upside and downside risk, idiosyncratic risk, and liquidity risk.*
- *Confirms the robustness of the comovement premium.*
- *Identifies interactions with other well-known risk factors.*

Contribution to literature and SDGs



The contribution to the Sustainable Development Goals (United Nations, 2015) is modest but not negligible.

This thesis could benefit goals such as SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation, and Infrastructure).

- Enhanced understanding of human behavior in stock markets could lead to
  - greater market stability
  - more accurate risk assessments for sustainable portfolios.

- Leveraging the Comove return premium could help generate capital to finance projects aligned with the Sustainable Development Goals.

Perceived Market Risk: from Sharpe to Ungeheuer & Weber

Sharpe (1964) defines the relationship between expected return of a stock and its systematic risk:

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

β_i represents the **sensitivity of the stock's return to market movements.** In practice, this is measured as correlation between historical returns of a stock and a market index.

The Perception of Dependence, Investment Decisions, and Stock Prices[a]

Michael Ungeheuer and Martin Weber[b]

Journal of Finance, forthcoming

Abstract

How do investors perceive dependence between stock returns? And how does their perception of dependence affect investments and stock prices? We show experimentally that investors understand differences in dependence, but not in terms of correlation. Participants invest as if applying a simple counting heuristic for the frequency of comovement. They diversify more when the frequency of comovement is lower even if correlation is higher due to dependence in the tails. Building on our experimental findings, we empirically analyze U.S. stock returns. We identify a robust return premium for stocks with high frequencies of comovement with the market return.

Ungeheuer and Weber (2020) propose frequency of comovement as an alternative measurement for market dependency and find a robust return premium in the U.S. market.

There is a **lack of empirical evidence** to support this model. Several explanations have been made:

1 Absence of additional variables: factor models

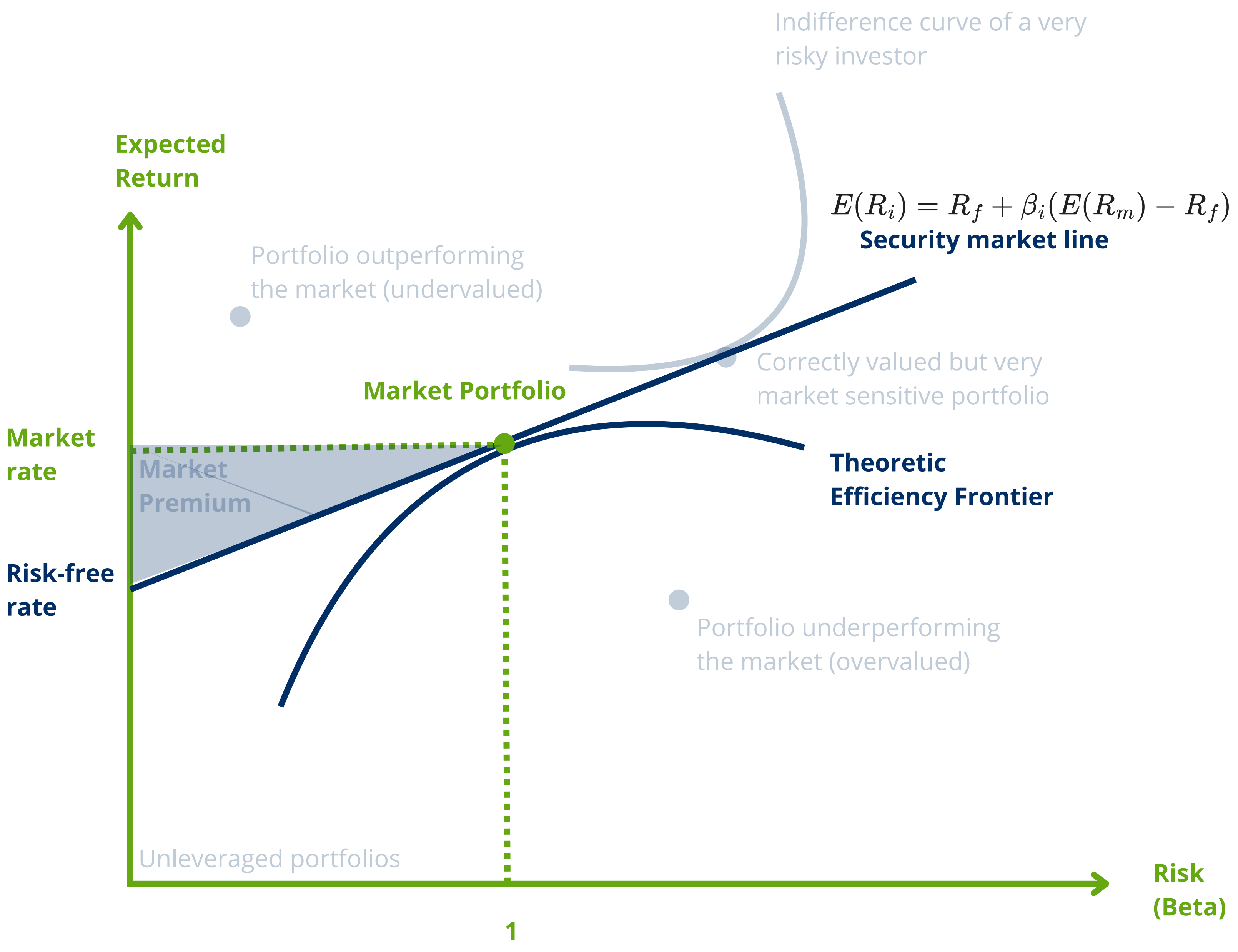
2 Unrealistic assumptions

3 Empirical testing difficulties: correlation neglect versus beta as unrealistic measurement

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

In the European stock market, stocks with a higher frequency of comovement between their returns and the market returns result in a return premium.

Introduction on the Capital Asset Pricing Model



Modern Portfolio Theory (Markowitz, 1952):

- Unsystematic risks of individual stocks can be mitigated by holding a diverse set of stocks in a portfolio.
- The efficiency frontier shows the portfolio with the highest expected return for a given level of risk.
- Further quantified in mean-variance analysis, which evaluates trade-off between risk (variance) and return (mean).

Capital Asset Pricing Model (Sharpe, 1964):

- Since the rest can be diversified away, only systematic risk is important in predicting asset prices.
- Beta measures the stock's market sensitivity. The higher beta, the higher the return.
- Linter (1965) had a similar idea.

Introduction on the Capital Asset Pricing Model

Assumption of the **mean-variance investor**: investors will make rational decisions about investments if they have complete information.

Markowitz: In other words, investors seek low risk and high reward.

- **Total risk is measured as variance**, and is a number that represents how varied or spread out the numbers are in a set.
- The expected return is a probability expressing the estimated return of the investment in the security.

A mean-variance investor seeks to construct an **optimal portfolio** by balancing expected return and risk. A mean-variance investor would choose a portfolio on the **Capital Market Line.**

If two different securities have the same expected return, but one has lower variance, the one with lower variance is the better pick. Similarly, if two different securities have approximately the same variance, the one with the higher return is the better pick.

Sharpe: Beta is used to understand how individual assets contribute to the overall portfolio's risk relative to the market. By combining assets with different betas, investors can achieve a desired level of portfolio risk.

For example, a conservative investor might choose assets with low betas to reduce volatility. Conversely, an aggressive investor might select high-beta assets to increase potential returns, accepting higher volatility.

Since all other risk can be diversified away, the Capital Asset Pricing Model focuses solely on systematic risk.

- **Systematic risk is measured as beta**, measuring the extent to which the returns of an asset (or portfolio) are expected to move in response to movements in the market as a whole.

A mean-variance investor would choose an **optimal individual asset or portfolio on the Security Market Line.**

Introduction on the Capital Asset Pricing Model

Beta specifically measures systematic risk, which is the risk inherent to the entire market or a particular market segment.

Beta is calculated using statistical regression analysis, where the returns of an asset are regressed against the returns of the market. The formula for beta is the correlation:

$$\beta_i = \frac{\text{Cov}(R_i, R_m)}{\text{Var}(R_m)}$$

This CAPM implies that an asset with a higher beta should offer a higher expected return to compensate for the higher systematic risk.

β_i

$\beta_i < 0$

An inverse exchange-traded fund (ETF) designed to move inversely to the market.

$\beta_i = 0$

A risk-free asset such as a short-term government bond.

$0 < \beta_i < 1$

A utility stock with a beta of 0.7.

$\beta_i = 1$

A large, diversified mutual fund that mirrors a market index.

$\beta_i > 1$

A technology stock with a beta of 1.5.

Introduction on the Capital Asset Pricing Model

Beta is not priced empirically.

Fama and French (1992): In coherence with earlier evidence, they find that market risk alone is not enough to explain the cross-sections of returns. They propose a three factor model.
Example: A size effect. Banz (1981) states that market equity also explains the cross-section of expected returns. Average returns on small (low ME) stocks are too high given their β estimates, and average returns on large stocks are too low.
Example: A value effect. Stattman (1980) finds that average returns on U.S. stocks are positively related to the ratio of a firm's book value of common equity, BE, to its market value, ME.

Later evidence also does not support the CAPM.
Example: Fama and French (2003) summarize (the lack of) empirical evidence on the CAPM. Celik (2012) reviews all asset pricing models theoretically and emprically.

I summarized the anomalies in three groups:

1. Factor Models
2. Critique on Assumptions
3. Empirical Testing Difficulties

Anomalies in the CAPM: Factor Models

Additional variables, beside market risk, can influence the expected return.

This led to the introduction of **multiple-factor models**.

- 3-Factor Model (Fama & French, 1993): Market Risk + Size + Value.
  - *Size: Small-Minus-Big. Smaller companies (by market capitalization) tend to have higher returns than larger companies.*
  - *Value: High-Minus-Low. Companies with high book-to-market ratios (value companies) tend to outperform those with low book-to-market ratios (growth companies).*

- 4-Factor Model (Carhart, 1997): Market Risk + Size + Value + Momentum.
  - *Momentum: Up-Minus-Down. Stocks that have performed well in the past ("winners") tend to continue performing well in the near future, and vice versa.*

- 5-Factor Model (Fama and French, 2015): Market Risk + Size + Value + Profitability + Investment.
  - *Profitability: Robust-Minus-Weak. Companies with higher profitability tend to have higher returns.*
  - *Investment: Conservative-Minus-Agressive. Companies with lower investment rates tend to have higher returns.*

- Q-Factor Model (Hou et al., 2015): Market Risk + Size + Profitability + Investment
  - *Uses the same factors, but measures these with other factors and without portfolio construction. For example, the Q-factor model uses the profitability factor (ROE) which is based on return on equity, whereas the Four-factor model uses the value factor (HML) which is based on the book-to-market ratio.*

Anomalies in the CAPM: Factor Models

Additional variables, beside market risk, can influence the expected return.

Individual additional factors are also proposed:

- *Betting-against-beta factor (Frazzini & Pederson, 2014): Stocks with lower beta tend to generate higher adjusted returns than predicted by CAPM.*
- *Tail risk factor (Kelly & Jiang, 2014): Stocks with higher exposure to tail risk tend to offer higher expected returns as compensation for the higher risk of extreme losses.*

- *Liquidity factor (Pastor & Stambaugh, 2001): Stocks that are less liquid (harder to buy or sell without affecting the price) tend to offer higher returns as compensation for the liquidity risk.*
- *Systemic liquidity factors (Sadka, 2003): Systemic liquidity risk refers to the risk that liquidity dries up across the entire market, affecting all securities. Stocks more sensitive to changes in market-wide liquidity conditions tend to offer higher returns to compensate for this risk.*

- *Mispricing factors (Stambaugh & Yuan, 2016): Market mispricings can lead to predictable return patterns as prices eventually correct as prices eventually correct. This paper focus on a wide array of anomalies to capture mispricing effects.*
- *Undervalued-minus-overvalued factor (Hirschleifer & Jiang, 2010): Market mispricings can lead to predictable return patterns as prices eventually correct. This paper focuses on valuation errors specifically, captured with portfolio construction.*

- *Financial health factor (Asness et al., 2007): Quality-Minus-Junk. High-quality stocks (measured by profitability, growth, safety, etc.) tend to outperform low-quality stocks.*

- *Carry factor (Koijen et al., 2016): The carry factor represents the returns from holding higher-yielding assets funded by shorting lower-yielding assets. This factor is prominent in currency and bond markets, where it captures the return premium from exploiting yield differentials across countries or securities.*

- *Seasonality factor (Keloharju et al., 2016): This factor captures predictable return patterns based on seasonal effects, such as the January effect or holiday-related anomalies. Stocks tend to exhibit seasonal return patterns that can be exploited for better investment strategies.*

- …

Anomalies in the CAPM: Factor Models

Additional variables, beside market risk, can influence the expected return

More general factor models have also been proposed:

- *Arbitrage Pricing Theory (Ross, 1976): Asset returns can be modeled as a linear function of factors, but these are not specified.*
- *Macro-factor and global factor models (Chen, 1986): Asset returns can be influenced by factors beyond specific markets or asset classes, such as inflation, shape of the yield curve, ...*
- *...*

Even with additional variables, there is **conflicting empirical evidence** for these factor models.
Example. Celik (2012) reviews all asset pricing models theoretically and empirically. Hwang and Lu (2007) suggest that many factors are redundant in asset pricing.

Anomalies in the CAPM: Unrealistic assumptions

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

Assumption 1: All investors hold a combination of the **market portfolio, containing all available assets and the risk-free asset.**

There is no risk-free asset.

- *DeJong & Collings (1985): There is no truly risk-free asset and even if such risk-free rate can be approximated, the rate would change over time.*
- *Friend & Blume (1970): There is a rate difference in risk-free borrowing and lending.*
- *Black (1972): Proposes a model with risk-free lending, but not borrowing.*

There is no market portfolio.

- *Roll (1977): The true market portfolio is unobservable as it should include all types of assets (e.g., stocks, bonds, real estate, human capital, ...).*
- *In practice, stock indexes are used as proxies. These do not capture the entire market.*

Anomalies in the CAPM: Unrealistic assumptions

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

Assumption 2: The **efficient market hypothesis** posits that investors have homogeneous expectations regarding returns and market sensitivities.

- *Markowitz (1992): All market participants are characterized as mean-variance investors who make decisions based solely on the expected returns (mean) and the variance of returns (risk) to maximize their utility.*

Investors don't have homogenous expectations.

- *Aghion et al. (2003): investors have diverse information and hold varying beliefs.*

Investors consider aspects beyond just mean and variance.

- *Factor models incorporate additional financial aspects.*
- *Behavioural finance fundamentally challenges the notion of a “homo economicus".*
- *Baker & Wulger (2006): Incorporate behavioural insights, such as investment sentiment, into a factor model.*
- *Correlation neglect.*

Anomalies in the CAPM: Unrealistic assumptions

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

Assumption 3: Only investments over **a single, upcoming time period** are to be considered.

The Intertemporal Capital Asset Pricing Model (Merton, 1973) 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.

Assumption 4: Investments occur in a **market without taxes, transaction costs, or restrictions on short selling**.

Different alternative factor models challenge this assumption.

- *Constantinides (1986): explores the impact of transaction costs on the capital market.*
- *Reilly and Brown (2001): suggest an alternative formula for the returns of stocks, since the rate of return used in the CAPM is before taxes.*
- *Pastor and Stambaugh (2001): incorporate liquidity as an additional factor, showing that there is priced liquidity risk to assets.*

Anomalies in the CAPM: Empirical testing difficulties

Empirical testing difficulties faced by the CAPM are underscored.

Already mentioned anomalies are examples of this problem.

- *Unobservable market portfolio.*
- *Theoretical emphasis on returns in one upcoming period.*
- *...*

Additionaly, there are discussions about beta.

Empirical evidence has shown that **beta is unstable over time**. This variability complicates the prediction of future returns using historical betas.

- *Blume (1971): He found that betas tend to regress towards the mean over time. This means that high beta stocks tend to decrease in beta, and low beta stocks tend to increase in beta as time progresses.*
- *Blume (1975): Due to this regression tendency, Blume suggests that historical betas should be adjusted when used for predicting future risks. Blume proposes a method for adjusting betas that involves using a weighted average of historical beta and the mean beta.*
- *Ferson & Harvey (1991): While beta coefficients do exhibit some time variation, the main source of predictability in asset returns comes from the time-varying risk premiums associated with these betas rather than the betas themselves.*
- *Jagannathan & Wang (1996): Jagannathan and Wang extended the CAPM by introducing conditional factors, showing that betas are not static but vary with economic conditions and firm-specific information.*

Anomalies in the CAPM: Empirical testing difficulties

Empirical testing difficulties faced by the CAPM are underscored.

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): This paper investigates how people often fail to account for correlations in information signals. The study shows that in financial markets, this neglect of correlation can lead to overoptimism and overpessimism, contributing to price bubbles and crashes.*
- *Eyster & Weizsacker (2016): This study examines correlation neglect in the context of portfolio choices. It finds that participants in laboratory experiments often ignore correlations between asset returns, leading to suboptimal diversification.*

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): The CAPM's pricing implications hold when market's participant's beliefs about beta are unbiased.*
- *Laudenbach et al. (2019): Better information presentation (e.g., a realistic sample format instead of descriptions of return distributions) can alleviate correlation neglect.*
- *Ungeheuer and Weber (2020): People fail to understand dependence in extreme returns and therefore misprice stocks.*

Correlation, return, and perceived dependence

Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

Participants were shown 100 return pairs of stock A and B.

- Participants were asked to articulate their beliefs about overall dependence, dependence in extreme returns and dependence in moderate returns.
- Participants were asked to allocate $10.000 between the two investment options.

In the experiments, only the return dependence is changed.

- Stock A has an average return of 5%.
- Stock B has an average return of 4%.

CAPM: Investors would diversify more in Stock B if correlation between stock A and B is lower.

Correlation, return, and perceived dependence

Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

Participants were shown 100 return pairs of stock A and B.

- Beliefs: participants were asked to articulate their beliefs about overall dependence, dependence in extreme returns and dependence in moderate returns.
- Choices: participants were asked to allocate $10.000 between the two investment options.

Two metrics were used to represent overall dependence of these stock returns. These metrics are varied across experiments.

- Correlation refers to the magnitude in which two returns move together.
- Frequency of comovement refers to the direction in which two returns move together (i.e., having the same sign).
  - Akin to a simple counting heuristic.
  - In comparison to correlation, this underweights extreme returns.

In the experiments, only the return dependence is changed.

- Stock A has an average return of 5%.
- Stock B has an average return of 4%.

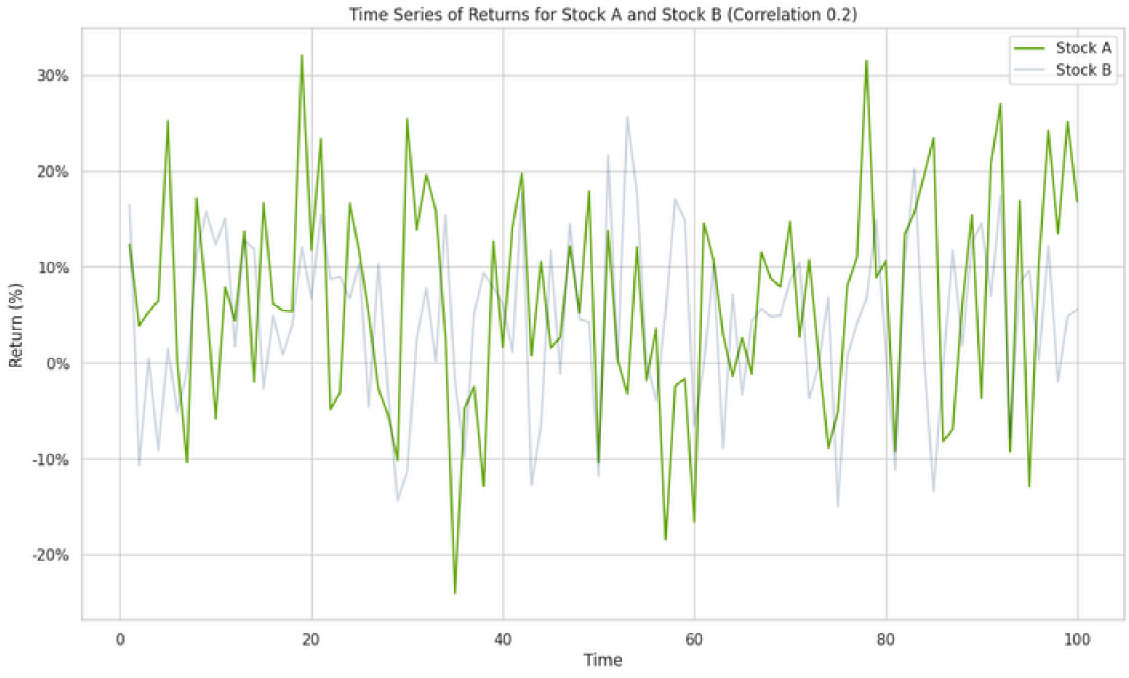
=> CAPM: Investors would diversify more in Stock B if correlation between stock A and B is lower.
=> This thesis: Investors would diversify more in Stock B if frequency of comovement between stock A and B is lower.

Correlation, return, and perceived dependence

Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

Experiment 1: Baseline. Lineair dependence which is the same for moderate and extreme returns.

Example of Treatment 1.
Correlation = -0.6



Example of Treatment 2.
Correlation = 0.2

Not 0, since positive returns are a bit more common in financial markets.

Example of Treatment 3.
Correlation = 0.6

Correlation, return, and perceived dependence

Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

Experiment 1: Baseline. Lineair dependence which is the same for moderate and extreme returns.

Correlation increases over treatments.
Frequency of comovement increases over treatments.

Beliefs on overall dependence increased over treatments.

- Beliefs on dependence of moderate returns correctly increased over treatments.
- Beliefs on dependence of extreme returns correctly increased over treatments.

Note that we cannot conclude that they understand both. They might just project the beliefs on dependence of moderate returns onto their beliefs on dependence of extreme returns! This is what we test in experiment 2 and 3.

All beliefs were biased towards 50%.

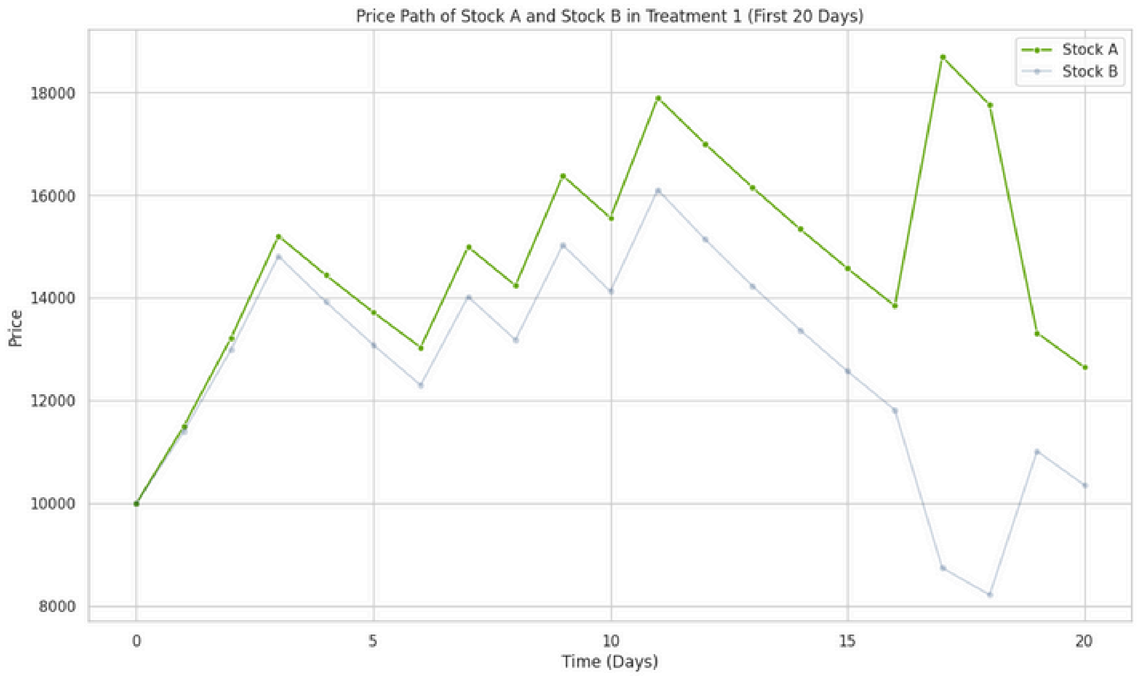
Diversifying decreased over treatments.

This is in line with CAPM and my thesis, which predicts that people would diversify less as correlation increases. This contradicts correlation neglect.

Correlation, return, and perceived dependence

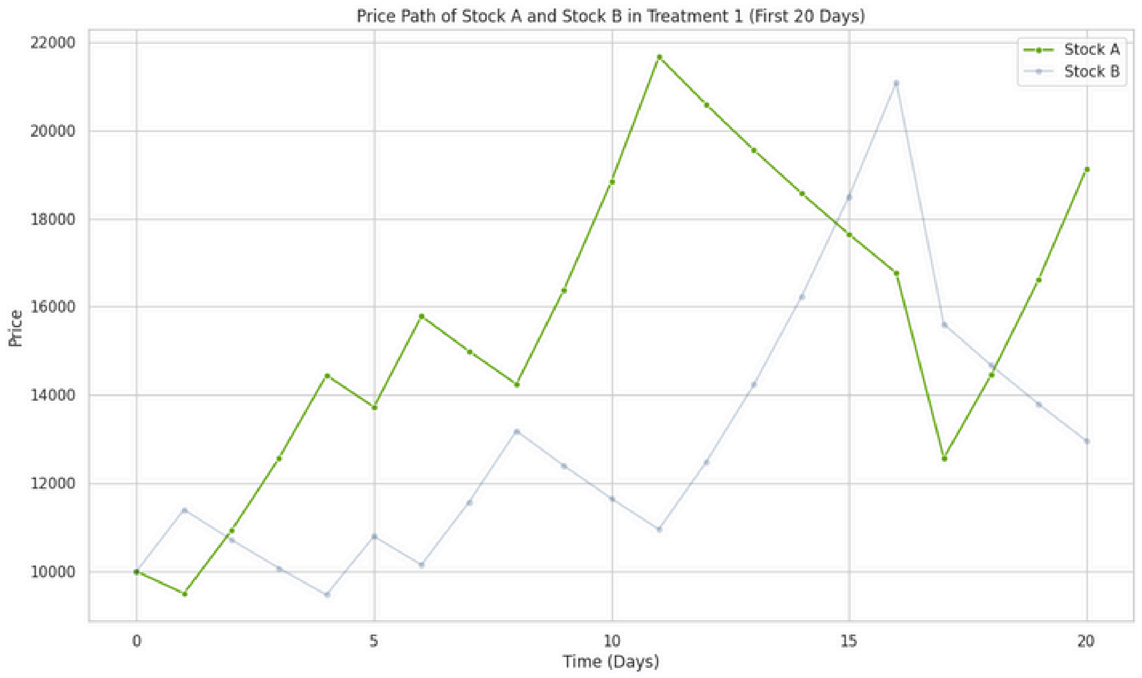
Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

Experiment 2: Initial evidence. No correlation. Contradicting dependence for moderate and extreme returns.



Example of Treatment 1.
Positive dependence in moderate returns.
Negative dependence in extreme returns.

Correlation = 0
Frequency of comovement = 0.90



Example of Treatment 2.
Negative dependence in moderate returns.
Positive dependence in extreme returns.

Correlation = 0
Frequency of comovement = 0.10

Correlation, return, and perceived dependence

Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

Experiment 2: Initial evidence. No correlation. Contradicting dependence for moderate and extreme returns.

Correlation is zero and stays constant over treatments.
Frequency of comovement decreases over treatments.

Beliefs on overall dependence decreased over treatments.

- Beliefs on dependence of moderate returns decreased over treatments.
- Beliefs on dependence of extreme returns has no significant difference over treatments.
  - Type 1: 18 out of 94 participants projected their beliefs and said that dependence of extreme returns decreased.
  - Type 2: 60 out of 94 participants said that they have no idea about the dependence of extreme returns.
  - Type 3: 16 out of 94 participants correctly understand dependency in extreme returns.

For overall dependence, they follow their beliefs on dependence of moderate returns. However, we cannot conclude that they do not understand dependence of extreme returns. Perhaps they choose to follow the moderate returns. This is why we also asked about beliefs on extreme returns seperately.

All beliefs were biased towards 50%.

Correlation, return, and perceived dependence

Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

Experiment 2: Initial evidence. No correlation. Contradicting dependence for moderate and extreme returns.

Correlation is zero and stays constant over treatments.
Frequency of comovement decreases over treatments.

Beliefs on overall dependence decreased over treatments.

- Beliefs on dependence of moderate returns decreased over treatments.
- Beliefs on dependence of extreme returns has no significant difference over treatments.

Diversifying increased over treatments.

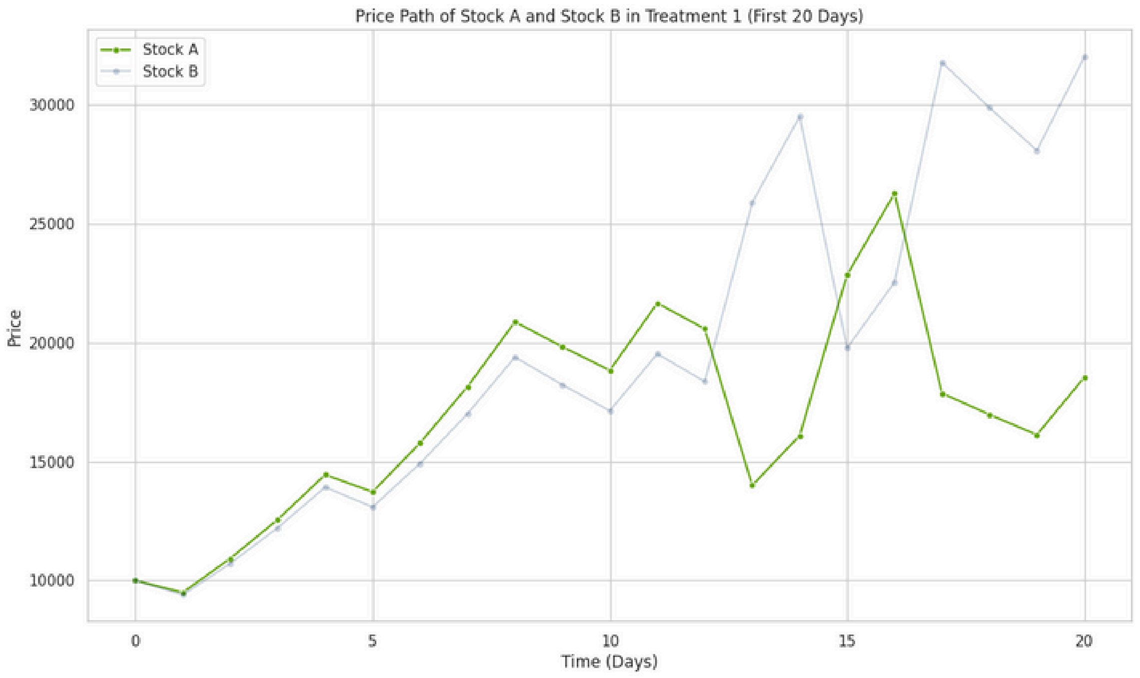
- Type 1: 18 out of 94 participants projected their beliefs and said that dependence of extreme returns decreased. As expected, they diversified more over treatments.
- Type 2: 60 out of 94 participants said that they have no idea about the dependence of extreme returns. We expect their beliefs to be driven by the understood dependence in moderate returns. As expected, they diversified more over treatments.
- Type 3: 16 out of 94 participants correctly understood dependency in extreme returns. Since their perception of dependence may be driven by both, it is not clear how they will make investment decisions. Surprisingly, they diversified (insignificantly) less over treatments.

As in my thesis, most people diversify more as their beliefs on moderate returns decreases. This is not in line with CAPM, which predicts that people would diversify similarly. This contradicts correlation neglect.

Correlation, return, and perceived dependence

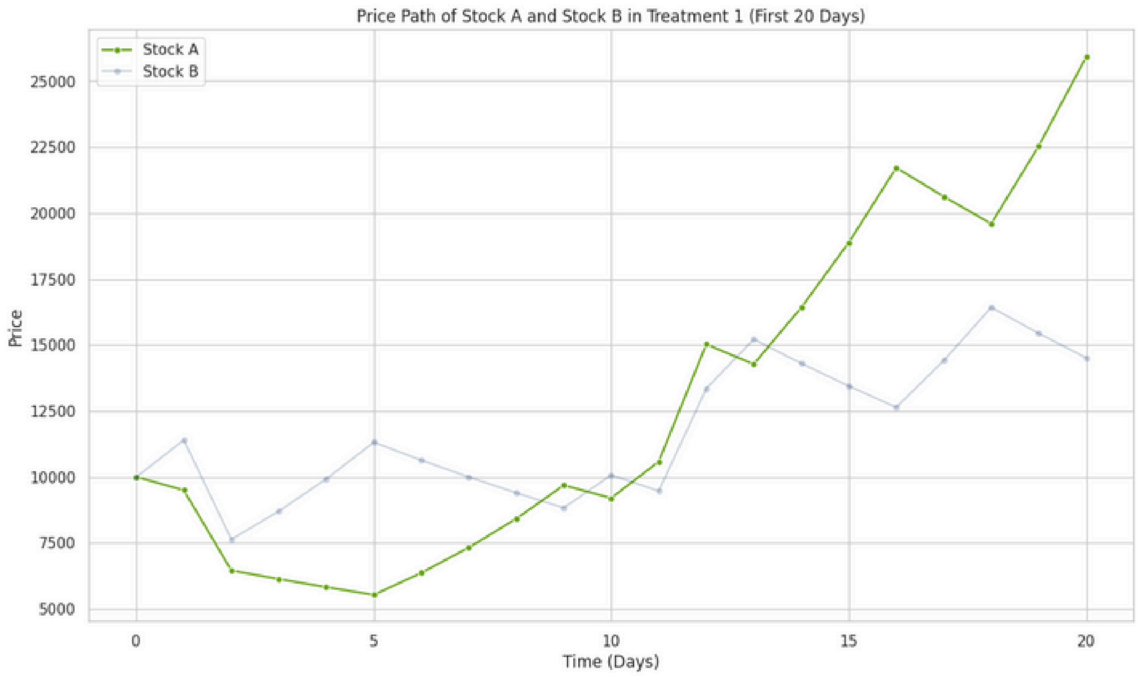
Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

Experiment 3: Acid test. Increasing correlation. Contradicting dependence for moderate and extreme returns. We make the marginal distributions of returns more extreme, comparable to historical extreme values.



Example of Treatment 1.
Positive dependence in moderate returns.
Negative dependence in extreme returns.

Correlation = -0.21
Frequency of comovement = 0.90



Example of Treatment 2.
Negative dependence in moderate returns.
Positive dependence in extreme returns.

Correlation = 0.21
Frequency of comovement = 0.10

Correlation, return, and perceived dependence

Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

Experiment 3: Acid test. Increasing correlation. Contradicting dependence for moderate and extreme returns. We make the marginal distributions of returns more extreme, comparable to historical extreme values.

Correlation increases over treatments.
Frequency of comovement decreases over treatments.

Beliefs on overall dependence decreased over treatments.

- Beliefs on dependence of moderate returns correctly decreased over treatments.
- Beliefs on dependence of extreme returns has no significant difference over treatments.
  - Type 1 and 2: 86 out of 107 participants projected their beliefs or had no idea, and said that dependence of extreme returns decreased.
  - Type 3: 21 out of 107 participants correctly understand dependency in extreme returns.

This is in line with the previous experiment. For overall dependence, they follow their beliefs on dependence of moderate returns. However, we cannot conclude that they do not understand dependence of extreme returns. Perhaps they choose to follow the moderate returns. This is why we also asked about beliefs on extreme returns seperately.

All beliefs were biased towards 50%.

Correlation, return, and perceived dependence

Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

Experiment 3: Acid test. Increasing correlation. Contradicting dependence for moderate and extreme returns. We make the marginal distributions of returns more extreme, comparable to historical extreme values.

Correlation increases over treatments.
Frequency of comovement decreases over treatments.

Beliefs on overall dependence decreased over treatments.

- Beliefs on dependence of moderate returns decreased over treatments.
- Beliefs on dependence of extreme returns has no significant difference over treatments.

Diversifying increased over treatments.

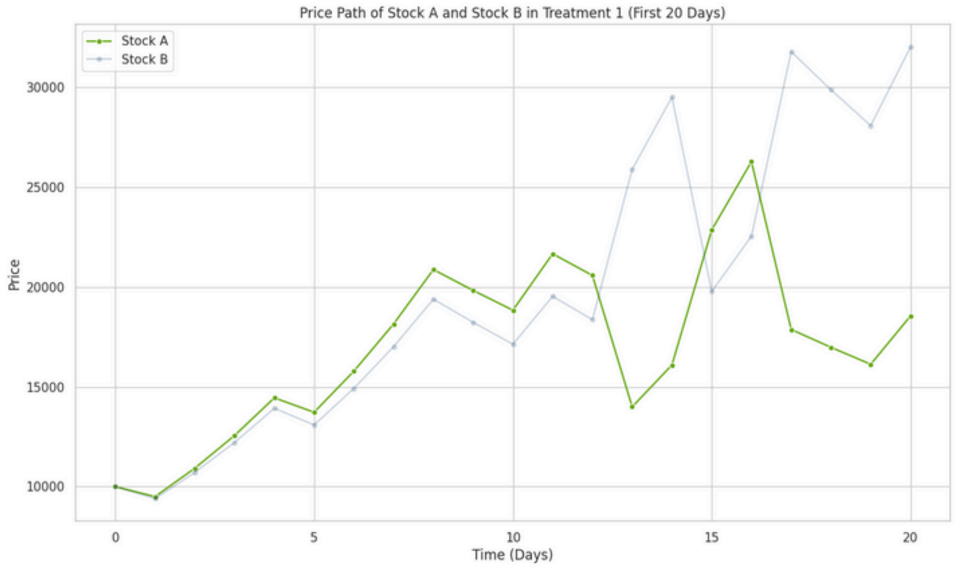
- *Type 1 and 2: 86 out of 107 participants projected their beliefs or had no idea, and said that dependence of extreme returns decreased. As expected, they diversified more over treatments.*
- *Type 3: 21 out of 107 participants correctly understand dependency in extreme returns. Since their perception of dependence may be driven by both, it is not clear how they will make investment decisions. Contrarily to the previous experiment, they also diversified (significantly) more over treatments.*

As in my thesis, all people diversify more as their beliefs on moderate returns decreases. This is not in line with CAPM, which predicts that people would diversify less as correlation increases. This contradicts correlation neglect.

Correlation, return, and perceived dependence

Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

Experiment 4: Robustness to presentation format. Increasing correlation. Contradicting dependence for moderate and extreme returns. We make the marginal distributions of returns more extreme, comparable to historical extreme values. Participants either got pricepaths or written returns.



Example of Treatment 1 for the price group.
Positive dependence in moderate returns.
Negative dependence in extreme returns.

Correlation = -0.21
Frequency of comovement = 0.90

-5%	-32%	-5%	-5%	-5%	15%	15%	15%	15%	-5%
+14%	-33%	14%	14%	14%	-6%	-6%	-6%	-6%	14%
15%	42%	-5%	15%	15%	15%	-5%	-5%	15%	15%
-6%	41%	14%	-6%	-6%	-6%	14%	14%	-6%	-6%

Example of Treatment 2 for the return group.
Negative dependence in moderate returns.
Positive dependence in extreme returns.

Correlation = 0.21
Frequency of comovement = 0.10

Correlation, return, and perceived dependence

Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

Experiment 4: Robustness to presentation format. Increasing correlation. Contradicting dependence for moderate and extreme returns. We make the marginal distributions of returns more extreme, comparable to historical extreme values. Participants either got pricepaths or written returns.

Correlation increases over treatments.
Frequency of comovement decreases over treatments.

Beliefs on overall dependence decreased over treatments.

- Beliefs on dependence of moderate returns decreased over treatments.
- Beliefs on dependence of extreme returns has no significant difference over treatments.

The return group understood extreme dependence better. Despite this better understanding of dependence in extreme returns, the return group's overall dependence assessment is still driven by dependence in moderate, frequent returns.

Similar results were found about beliefs in the other experiments.

Correlation, return, and perceived dependence

Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

Experiment 4: Robustness to presentation format. Increasing correlation. Contradicting dependence for moderate and extreme returns. We make the marginal distributions of returns more extreme, comparable to historical extreme values. Participants either got pricepaths or written returns.

Correlation increases over treatments.
Frequency of comovement decreases over treatments.

Beliefs on overall dependence decreased over treatments.

- Beliefs on dependence of moderate returns decreased over treatments.
- Beliefs on dependence of extreme returns has no significant difference over treatments.
  - *The return group understood extreme returns better, but this had no impact on the beliefs of overall dependence.*

Diversifying increased over treatments.

- Type 1 and 2: Participants projected their beliefs or had no idea, and said that dependence of extreme returns decreased. As expected, they diversified more over treatments.
  - *The return group diversified most.*
- Type 3: Participants correctly understand dependency in extreme returns. Since their perception of dependence may be driven by both, it is not clear how they will make investment decisions.
  - *As in experiment 2 and surprisingly, the price group diversified (insignificantly) less over treatments. Those who view price paths form beliefs about overall dependence closer to dependence in the tails and choose to diversify away variations in tails.*
  - *As in experiment 3 and in line with our hypothesis, the return group diversified (significantly) more over treatments. Participants who view return series form beliefs about overall dependence driven by moderate dependence and choose to diversify away moderate variations.*

As in my thesis, most people diversify more as their beliefs on moderate returns decreases. This is not in line with CAPM, which predicts that people would diversify less as correlation increases. This contradicts correlation neglect.

Given the choice of viewing prices or returns as in experiments 1, 2, and 3 (and often in reality), participants' investment choices are similar to choices when they only view return series.

Correlation, return, and perceived dependence

Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

Conclusions on **correlation and perceived dependence**.

	Overall dependence (correlation)	Dependence in moderate returns (frequency of comovement)	Dependence in extreme returns	Beliefs about overall dependence	Beliefs about dependence in moderate returns	Beliefs about dependence in extreme returns	Expected behaviour under CAPM	Expected behaviour under their hypothesis	Actual investment behaviour
Experiment 1	↗	↗	↗	↗	↗	↗	↘	↘	↘
Experiment 2	=	↘	↗	↘	↘	Type 1: ↘ Type 2: ? Type 3: ↗	=	Type 1 & 2: ↗ Type 3: ?	Type 1 & 2: ↗ Type 3: ↘
Experiment 3	↗	↘	↗	↘	↘	Type 1: ↘ Type 2: ? Type 3: ↗	↘	Type 1 & 2: ↗ Type 3: ?	Type 1 & 2: ↗ Type 3: ↗
Experiment 4 (Price group)	↗	↘	↗	↘	↘	Type 1: ↘ Type 2: ? Type 3: ↗ ! More in return	↘	Type 1 & 2: ↗ Type 3: ?	Type 1 & 2: ↗ Type 3: ↘
Experiment 4 (Return group)									Type 1 & 2: ↗ ! More in return. Type 3: ↗

Correlation, return, and perceived dependence

Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

Conclusions on **correlation and perceived dependence**.

- 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.**

- 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, contradiction a mean-variance investment strategy.

Correlation, return, and perceived dependence

Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

From lab to reality. Even if many people acted as the participants, Ungeheuer and Weber (2020) were not sure if their investment behavior could drive prices.

  - *NO: One might say that an institutionalized investor could exploit this bias, and this would wash out any price effect on the aggregate demand. For example, Bossaerts & Plot (2004) show that individual investors are not close to "the market" but that the aggregate demand is in line with CAPM.*
  - *YES: There have has been empirical effects on returns. Even if such an offsetting demand exists, it it nog enough to prevent price impact of perceived dependence.*
  - *YES: Empirical asset pricing shows that systematic behaviour on a individual level can affect prices due to limits of arbitrage. For example, Barberis et al. (2016) that stocks with historical positive returns become overvalued because of how people perceive losses and gains.*

- 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.

Correlation, return, and perceived dependence

Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

From lab to reality. Even if many people acted as the participants, Ungeheuer and Weber (2020) were not sure if their investment behavior could drive prices.

Ungeheuer and Weber (2020) analyzed U.S. common shares from the NYSE, AMEX, and NASDAQ from 1963 to 2015 to test this hypothesis.

In the main tests, some data is excluded:

- *Stocks below $1: to avoid microstructure issues.*
- *Firms that are small: market capitalization is below the 10th NYSE percentile*

In the robustness tests, it is shown that the findings are not dependent on these decisions.

- *Excluding NASDAX stocks*
- *Including the 1927-1962 period before the main sample*
- *Excluding stocks with prices below $5*
- *Including small firms*

Correlation, return, and perceived dependence

Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

From lab to reality. Even if many people acted as the participants, Ungeheuer and Weber (2020) were not sure if their investment behavior could drive prices.

Main variable Comove:
The % of weeks were the weekly stock return ri and the weekly S&P500 return rm had the same sign, in the last 52 weeks.

- *Using the popular S&P500 as market return makes sense, since its returns are highly visible. Robustness show that we have similar findings if we use CRSP's value-weighted market returns.*
- *Using weekly returns in a one-year horizon is natural in this context. Robustness show that we have similar findings if we use the last 260 daily returns (1 year in business days) or the last 36 monthly returns (3 years).*

Control variable Beta:
Historical correlations of the last 260 daily returns of the stock and the S&P500.

- *Using daily returns in a one-year horizon is common in this context. Robustness show that we have similar findings if we use the last 52 weekly returns (1 year in business days) or the last 36 monthly returns (3 years).*

Stocks are double-sorted into portfolios - first on beta and then on comove. Average return and comove is calculated per portfolio.

Correlation, return, and perceived dependence

Ungeheuer and Weber (2020) propose the **frequency of comovement of stocks instead of correlation as a measurement for perceived dependence**.

Conclusions on **return and perceived dependence**.

- 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.

Double-sorting individual stocks into monthly portfolios

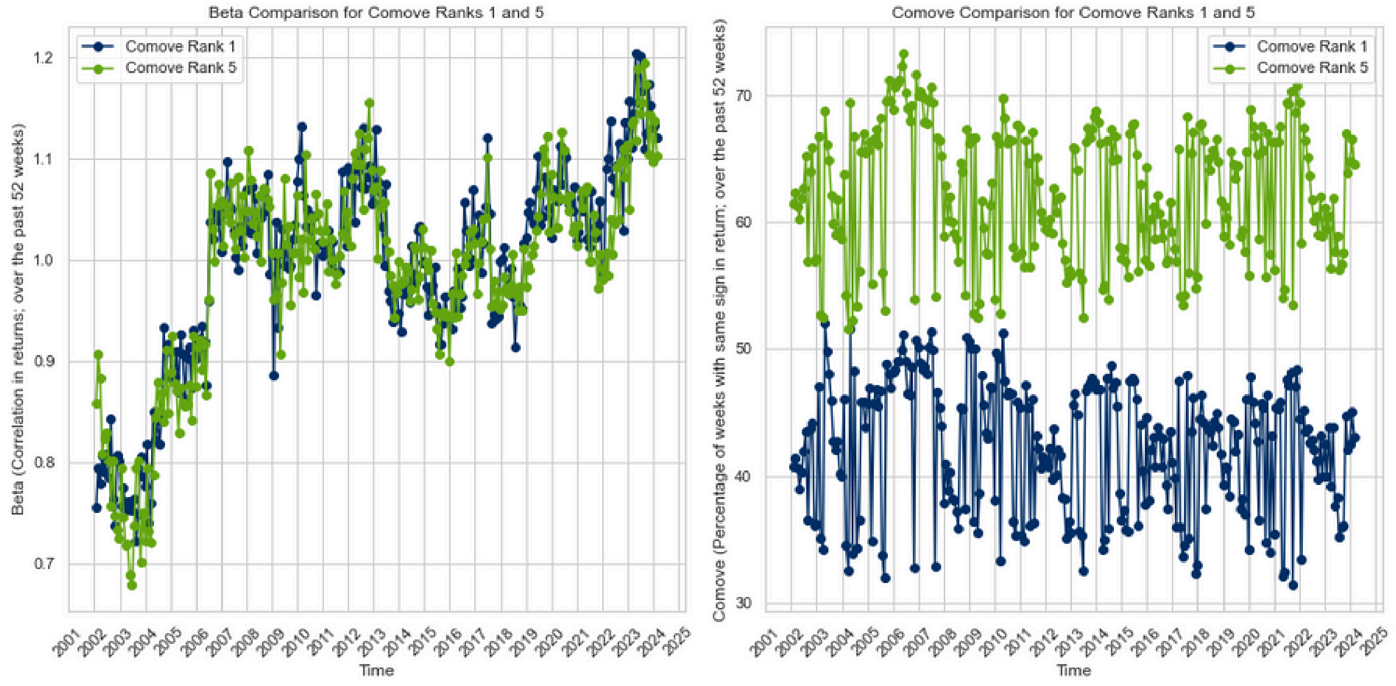
Data is retrieved from **DataStream** software in euros. The monthly market return is represented by the **STOXX Europe 600** index. Portfolios are formed from stocks that are constituents of this index during each respective month. The individual stock returns are calculated based on their performance during the month, while the beta and frequency of comovement are determined using returns from the 52 weeks preceding each month.

Organization of stocks into **five distinct portfolios each month**, each characterized by a strong exposure to Comove while holding Beta relatively constant across portfolios.

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

Illustration of time intervals used in the definition of variables for individual stocks. An example is given for the month January [Table 2].



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

Methodology

Data Collection of Main Variables. The main variables are calculated on the level of an individual stock and are all based on the return index in euro from DataStream software.

Why? The variables are calculated on a monthly basis. Portfolios are formed from stocks that are constituents of EUR600 index during the respective month.

What? DataStream's return index is the theoretical absolute growth in value of a share holding over that day, assuming that dividends are re-invested to purchase additional unites of the stock at the closing price applicable on the ex-dividend date. Note that these “prices” are converted to euro.

Close

RI - Total Return Index

Explorers: Equities » Key Datatypes
Equities » Datastream » Time Series » Pricing

Actions: Add to My Selections

Notes: A return index (RI) is available for individual equities and unit trusts. This shows a theoretical growth in value of a share holding over a specified period, assuming that dividends are re-invested to purchase additional units of an equity or unit trust at the closing price applicable on the ex-dividend date. .

For all countries except the USA and Canada detailed dividend payment data is only available on Datastream from 1988 onwards. Up to this time the RI is constructed using the annualised dividend yield. This method adds an increment of 1/260th part of the dividend yield to the price each weekday. There are assumed to be 260 weekdays in a year, market holidays are ignored:

Method 1 (using annualised dividend yield)

RI on the basedate =100, then:

$$RI_t = RI_{t-1} * \frac{PI_t}{PI_{t-1}} * \left(1 + \frac{DY_t}{100} * \frac{1}{N}\right)$$

Where:

RI_t = return index on day t

RI_{t-1} = return index on previous day

PI_t = price index on day t

PI_{t-1} = price index on previous day

DY_t = dividend yield % on day t

N = number of working days in the year (taken to be 260)

Methodology

Data Collection of Main Variables. The main variables are calculated on the level of an individual stock and are all based on the return index in euro from DataStream software.

How?

Step 1: The return index is retrieved from DataStream. The correct prompts are loaded with the given process table or by generating the excel file with the prompts per sheet by running the given notebook.

Code for STOXX EUR 600

Code for return index of this index.

Daily frequency.

Prompt for index:

= DSGRID("DJSTOXX”; “RI”; “1999-01-01”;"2024-03-31";"D”;"LayoutArg")

Prompt for stocks: in each quarter,

Prefix L gives consituents of an index

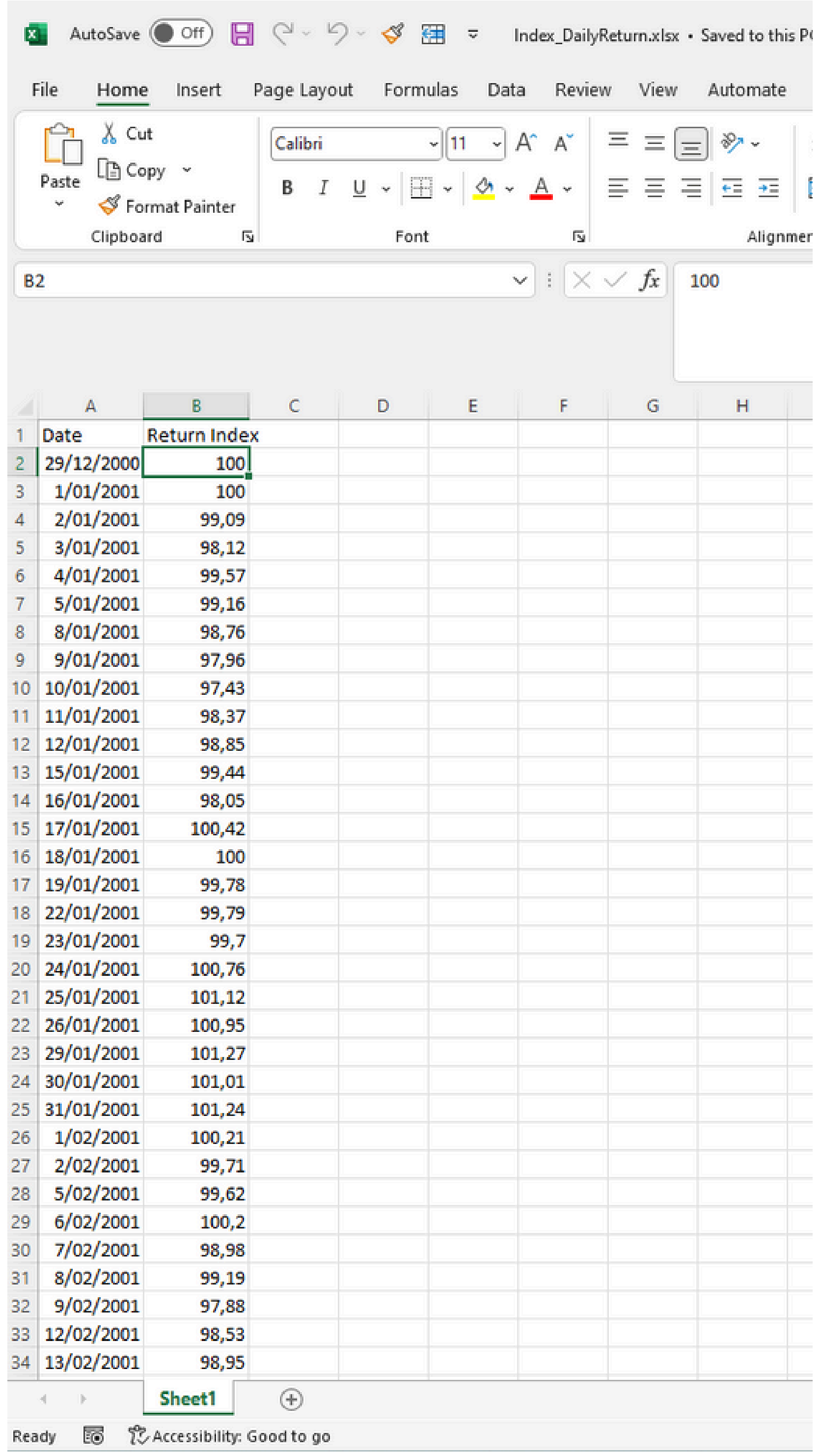
Return index should be converted to euro, as some stocks are listed in British Pounds, Swiss Francs, …

= DSGRID("LDJSTOXXMMYY”; “X(RI)~E”; “startDate”;"endDate";"D”;"LayoutArg")

Constituents index at this month. With MMYY the first month of each quarter, with the months ranging from 0102 until 0324.

With startDate and endDate in YYYY-MM-DD format; startDate the first day of the year prior to MMYY and endDate the last day of two months after the MMYY. For example, for Jan 2002, 2001-01-01 and 2002-03-31.

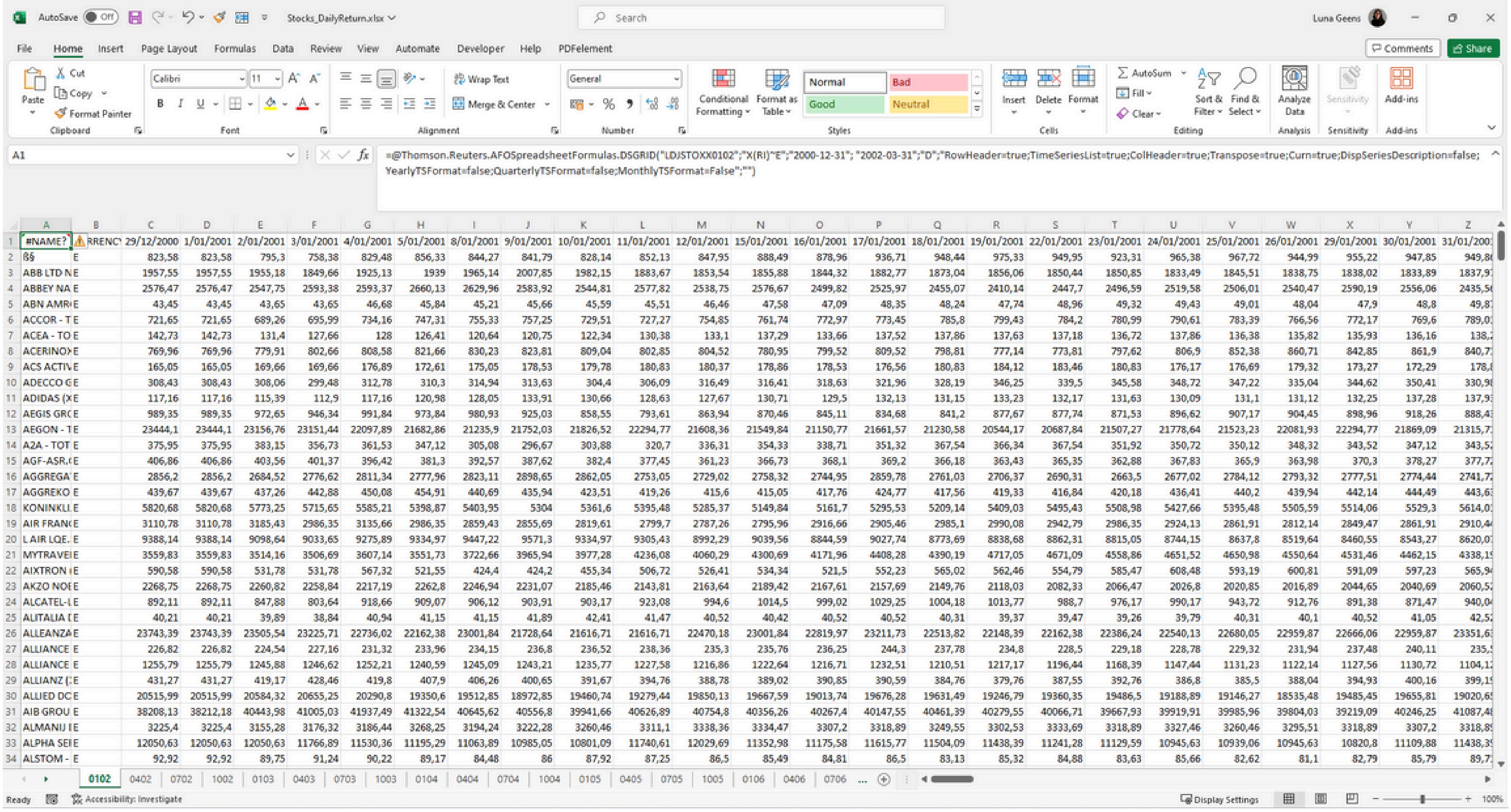
Methodology



Date	Return Index
29/12/2000	100
1/01/2001	100
2/01/2001	99,09
3/01/2001	98,12
4/01/2001	99,57
5/01/2001	99,16
8/01/2001	98,76
9/01/2001	97,96
10/01/2001	97,43
11/01/2001	98,37
12/01/2001	98,85
15/01/2001	99,44
16/01/2001	98,05
17/01/2001	100,42
18/01/2001	100
19/01/2001	99,78
22/01/2001	99,79
23/01/2001	99,7
24/01/2001	100,76
25/01/2001	101,12
26/01/2001	100,95
29/01/2001	101,27
30/01/2001	101,01
31/01/2001	101,24
1/02/2001	100,21
2/02/2001	99,71
5/02/2001	99,62
6/02/2001	100,2
7/02/2001	98,98
8/02/2001	99,19
9/02/2001	97,88
12/02/2001	98,53
13/02/2001	98,95

Data Collection of Main Variables. The main variables are calculated on the level of an individual stock and are all based on the return index in euro from DataStream software.

Step 2: Running those prompts gives u an Excelfile Stocks_DailyReturn.xlsx with sheets per quarter and an Excelfile Index_DailyReturn.xslx containing the absolute return index. In the Jupyter Notebook file Data_Monthly.ipynb, both excels are read in as panda dataframes.



Methodology

Data Collection of Main Variables. The main variables are calculated on the level of an individual stock and are all based on the return index in euro from DataStream software.

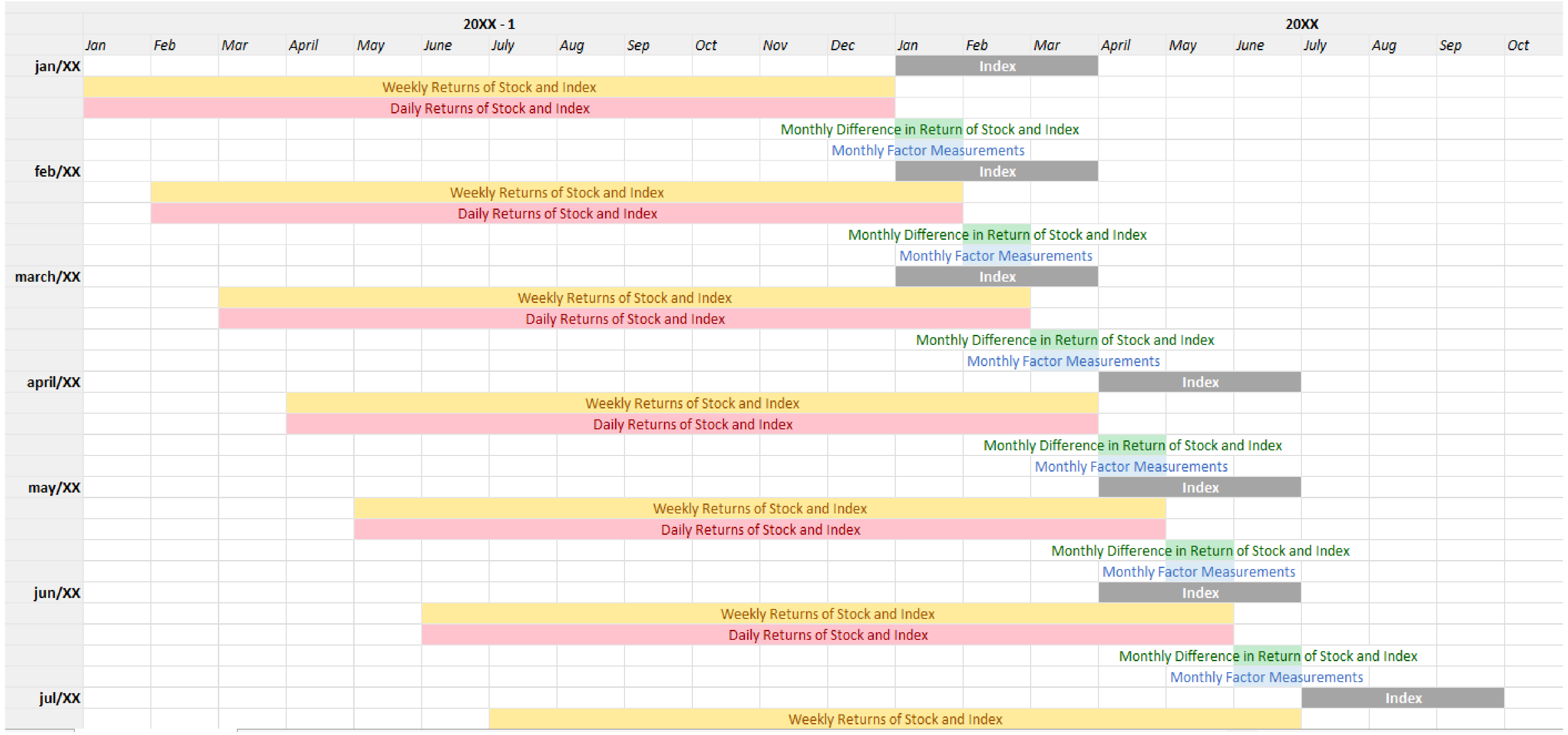
Step 3: The return index from dataStream is manipulated. The dates.xlsx file helps me to identify the correct return indexes per month.

The return index from dataStream software is retrieved per quarter, since the constituents of the EUR600 index only change each quarter.
Example. For the months January, February and March 2002, the relevant return indexes can be found in an excel sheet or dataframe called 0102 (Index).

The return index from dataStream software is absolute. The return index is only given on workdays. 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.
Example. The month June 2002 starts on Sat. 1 June 2002 (StartMonth) and ends on Sun. 30 June (EndMonth). The first absolute return we have for that month will be the return index on Mon. 3 June 2002 (StartMonth_Weekday). The last absolute return we have for that month will the return index on Fri. 28 June 2002 (EndMonth_Weekday). Let's now say i want to calculate the relative return index to see how the stock performed in this month. I need to compare the last return index of this month, on Fri. 28 June 2002, with the last return index of the previous moth, Fri. 31 May 2002 (StartMonthMinus1_Weekday).

Month	Year	Index	StartMonth	StartMonth	StartMonthMinus1	StartMonthMinus1_Weekday	EndMonth	EndMonth_Weekday	StartPastYear	StartPastYear_Weekday	StartPastYearMinus1	StartPastYearMinus1_Weekday	EndPastYear	EndPastYear_Weekday
1	2002	0102	1/01/2002	1/01/2002	31/12/2001	31/12/2001	31/01/2002	31/01/2002	1/01/2001	1/01/2001	31/12/2000	29/12/2000	31/12/2001	31/12/2001
2	2002	0102	1/02/2002	1/02/2002	31/01/2002	31/01/2002	28/02/2002	28/02/2002	1/02/2001	1/02/2001	31/01/2001	31/01/2001	31/01/2002	31/01/2002
3	2002	0102	1/03/2002	1/03/2002	28/02/2002	28/02/2002	31/03/2002	29/03/2002	1/03/2001	1/03/2001	28/02/2001	28/02/2001	28/02/2002	28/02/2002
4	2002	0402	1/04/2002	1/04/2002	31/03/2002	29/03/2002	30/04/2002	30/04/2002	1/04/2001	2/04/2001	31/03/2001	30/03/2001	31/03/2002	29/03/2002
5	2002	0402	1/05/2002	1/05/2002	30/04/2002	30/04/2002	31/05/2002	31/05/2002	1/05/2001	1/05/2001	30/04/2001	30/04/2001	30/04/2002	30/04/2002
6	2002	0402	1/06/2002	3/06/2002	31/05/2002	31/05/2002	30/06/2002	28/06/2002	1/06/2001	1/06/2001	31/05/2001	31/05/2001	31/05/2002	31/05/2002
7	2002	0702	1/07/2002	1/07/2002	30/06/2002	28/06/2002	31/07/2002	31/07/2002	1/07/2001	2/07/2001	30/06/2001	29/06/2001	30/06/2002	28/06/2002
8	2002	0702	1/08/2002	1/08/2002	31/07/2002	31/07/2002	31/08/2002	30/08/2002	1/08/2001	1/08/2001	31/07/2001	31/07/2001	31/07/2002	31/07/2002
9	2002	0702	1/09/2002	2/09/2002	31/08/2002	30/08/2002	30/09/2002	30/09/2002	1/09/2001	3/09/2001	31/08/2001	31/08/2001	31/08/2002	30/08/2002

Methodology



Data Collection of Main Variables. The main variables are calculated on the level of an individual stock and are all based on the return index in euro from DataStream software.

Step 4: Main variables are calculated from this absolute daily return indexes. Each main variable needs different frequencies on different time periods.

Methodology

Data Collection of Main Variables. The main variables are calculated on the level of an individual stock and are all based on the return index in euro from DataStream software.

Step 4: Main variables are calculated from this absolute daily return indexes. Each main variable needs different frequencies on different time periods.

For monthly return of an individual stock:

- The daily absolute return index of StartMonthMinus1_Weekday and EndMonth_Weekday are retrieved.
- The percentual difference between the two is calculated:

Monthly Return of Stock i in month t

Last available absolute return index of Stock i in month t

Last available absolute return index of Stock i before month t

$$Return_{i,t,monthly} = \frac{Return_{i,EndMonthWeekday} - Return_{i,StartMonthMinus1Weekday}}{Return_{i,EndMonthWeekday}}$$

Methodology

Data Collection of Main Variables. The main variables are calculated on the level of an individual stock and are all based on the return index in euro from DataStream software.

Step 4: Main variables are calculated from this absolute daily return indexes. Each main variable needs different frequencies on different time periods.

For monthly frequency of comovement of a stock:

- Both for stocks and EUR600 index: The daily absolute return indexes in the past year are retrieved, starting from StartPastYearMinus1_Weekday until EndPastYear_Weekday.

- Both for stocks and EUR600 index: The daily absolute return indexes in the past year are aggravated into weekly absolute return indexes by taking the average.

- Both for stocks and EUR600 index: The weekly percentual difference is calculated, starting from StartPastYear until EndPastYear.
    - *For the first week of the past year, the relative difference is taken by comparing its return with the daily absolute return on StartPastYearMinus1_Weekday.*

- Calculate the frequency of comovement of a stock between the 53 relative returns of the stock and the 52 relative daily returns of the EUR600 as the percentage of weeks where the the return of the individual stock and the EUR600 index had the same sign.

Methodology

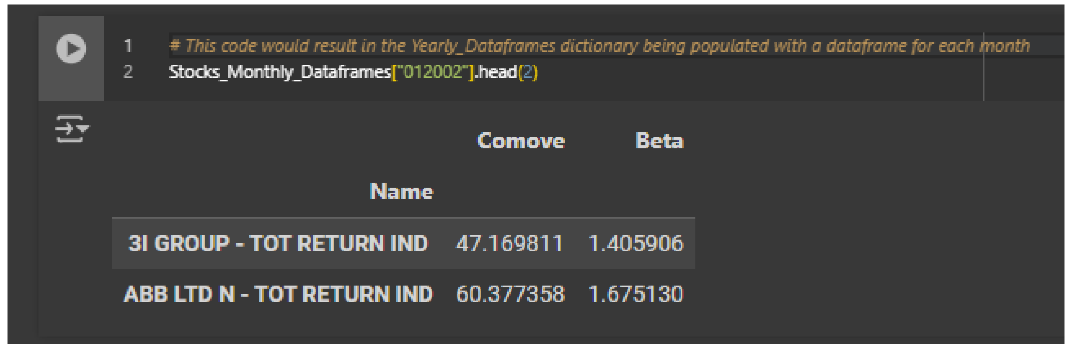
Data Collection of Main Variables. The main variables are calculated on the level of an individual stock and are all based on the return index in euro from DataStream software.

Step 4: Main variables are calculated from this absolute daily return indexes. Each main variable needs different frequencies on different time periods.

For monthly beta of a stock:

- Both for stocks and EUR600 index: The daily absolute return indexes in the past year are retrieved, starting from StartPastYearMinus1_Weekday until EndPastYear_Weekday.
- Both for stocks and EUR600 index: The day-on-day percentual difference is calculated, starting from StartPastYear until EndPastYear.
  - *Notice that this is not always the percentual difference between two consecutive days. For example, relative returns on Monday are the equal to the growth in absolute returns on that Monday and last Friday.*
  - *For the first day of the past year, the relative difference is taken by comparing its return with the daily absolute return on StartPastYearMinus1_Weekday.*
- Calculate the correlation between the 260 relative returns of the stock and the 260 relative daily returns of the EUR600:

$$\beta_i = \frac{\mathrm{Cov}(R_i, R_m)}{\mathrm{Var}(R_m)}$$



```
# This code would result in the Yearly_Dataframes dictionary being populated with a dataframe for each month
Stocks_Monthly_Dataframes["012002"].head(2)
```

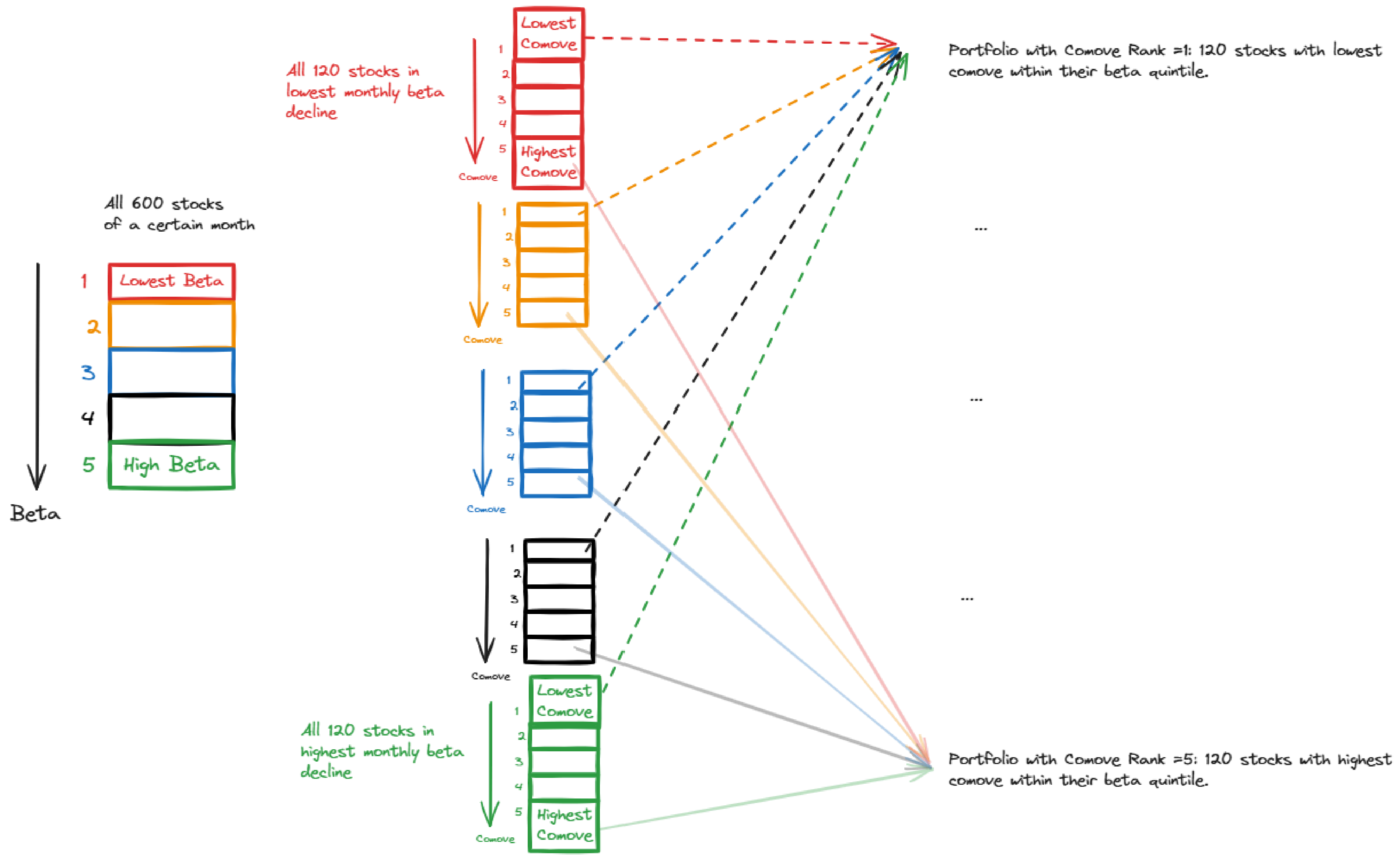
Name	Comove	Beta
3I GROUP - TOT RETURN IND	47.169811	1.405906
ABB LTD N - TOT RETURN IND	60.377358	1.675130

Methodology

Data Sorting. Having the variables of individual stocks, stocks are now sorted into five portfolio's per month.

Step 1: Rank the stocks on beta. Divide the stocks into quintiles based on their beta value. Add a additional column called Beta rank where each stock gets a number between 1 and 5, based on the quintile they are in. This is 1 indicating the quintile with the lowest betas and 5 the highest.

Step 2: For each quintile, filter the dataframe for only stocks within this quintile. Rank the filtered stocks on Comove. Divide the filtered stocks into quintiles based on their comove value. Add a additional column to the intial dataframe called Comove rank where each stock gets a number between 1 and 5, based on the quintile they are in. This is 1 indicating the quintile with the lowest comove and 5 the highest within each beta quintile.



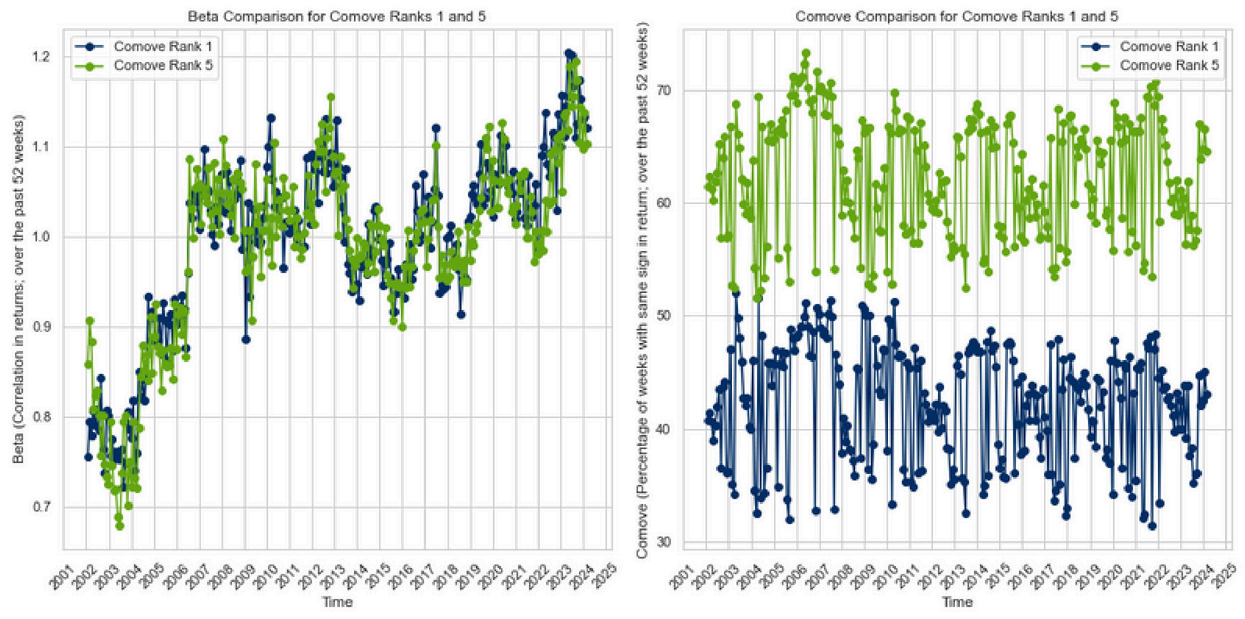
Methodology

Data Sorting. Having the variables of individual stocks, stocks are now sorted into five portfolio's per month.

Step 3: We can use the Comove rank column to define our portfolio's for each month.

- For every comove rank of this month, we calculate the average comove and return of all stocks in that portfolio.
- Apart from the mean, we also calculate the standard deviation of beta and comove of stocks in that portfolio.

By sorting in this matter, we have a strong exposure to Comove while holding Beta relatively constant across portfolio's.



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

	Avg.(Beta of portfolio)	*Avg.(Comove of portfolio)*
Lowest Comove Portfolio	*0.9930*	*42.2978*
Highest Comove Portfolio	*0.9871*	*62.3631*
Difference	*+ 0.0059* *= + 0.59%* *= **300.89% of Beta's standard deviation** (0.00020)*	*+20.07* *= + 47,4382%* *= **3 921.26% of Comove's standard deviation** (-0.5177)*

Methodology

Data Sorting. Having the variables of individual stocks, stocks are now sorted into five portfolio's per month. Factor data is then added per month and the final dataframe is written away to an excelfile named Monthly Data.xlsx.

```
# At this point, each DataFrame in Monthly_Dataframes has been updated with 'Beta rank' and 'Comove rank' columns.
Stocks_Monthly_Dataframes['012002'].head(2)  # For the year 2023 data
```

Name	Comove	Beta	Return	Beta rank	Comove rank
3I GROUP - TOT RETURN IND	47.169811	1.405906	-10.499001	5	1
ABB LTD N - TOT RETURN IND	60.377358	1.675130	-7.529581	5	5

```
# Display the final dataframe
final_df
```

	MMYYYY	Avg. Comove	Comove rank	HighestComove_Dummy	Avg. Beta	Avg. Return
0	012002	40.776435	1	0	0.754675	1.038957
1	012002	47.036102	2	1	0.852650	-1.133048
2	012002	50.648072	3	1	0.813622	0.657551
3	012002	53.959039	4	1	0.819501	-0.573638
4	012002	61.450240	5	1	0.857848	-1.517494
...	...	...	...	...	...	...
1325	022024	43.063263	1	0	1.121668	-0.610936
1326	022024	50.356394	2	1	1.170942	-0.523685
1327	022024	54.491951	3	1	1.196805	0.776255
1328	022024	58.898113	4	1	1.056555	1.371779
1329	022024	64.552389	5	1	1.103318	5.160275

1330 rows × 6 columns

Methodology

Autocorrelation. An Autoregressive (AR) process is a type of stochastic time series model in which the current value of the series is based on the past values.

The simplest form of an AR model is the AR(1) model, where the current value of the series Yt is based on the immediately preceding value Yt−1 plus a stochastic error term et:

$$Y_t = \phi Y_t - 1 + e_t$$

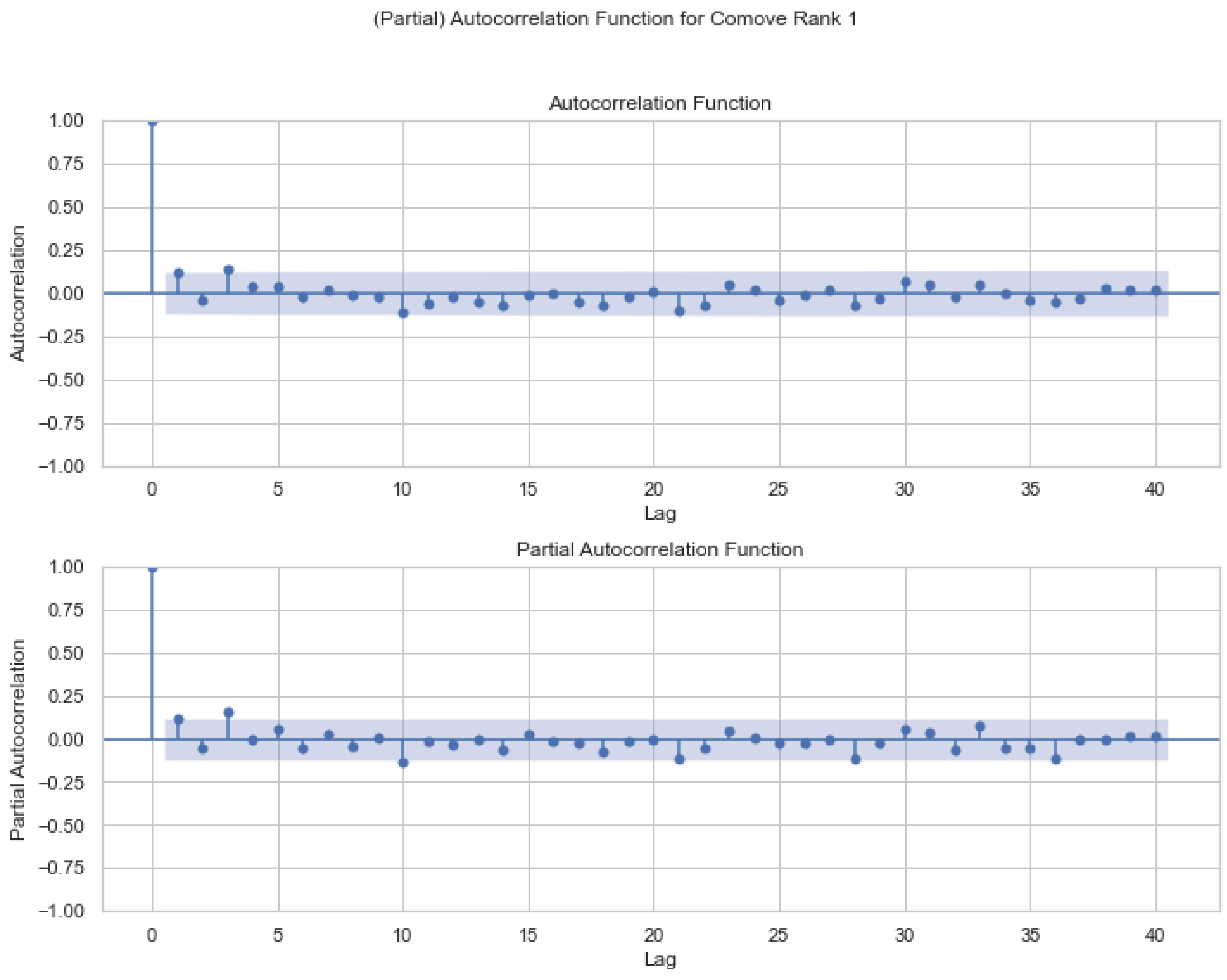
Here, ϕ (phi) is a parameter that measures the influence of the past value on the current value.

For an AR(p) model, the current value depends on the previous p values:

$$Y_t = \phi_1 Y_t - 1 + \phi_2 Y_t - 2 + \ldots + \phi_p Y_t - p + e_t$$

We will determine the value of p in our return variable using different methods.

Methodology



Autocorrelation. An Autoregressive (AR) process is a type of stochastic time series model in which the current value of the series is based on the past values.

First, let's look at the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) per Comove Rank. Note that is is logical that the Comove ranks have the same ACF and PACF, since they should have the same time-dependency.

ACF: how the time series is correlated with its own past values (lags).

- *The correlation drops sharply after lag 0. Correlations for subsequent lags stay within the confidence bounds, except for 1 and 3.*
- *This means there is a strong correlation at lag 0, and some possible repeating patterns, though they are not statistically significant (as they stay within the confidence bounds).*

PACF: how the time series is correlated with its the previous value (lag), removing the effects of previous lags.

- *A significant spike at lag 1 and 3, just outside the confidence bounds, suggesting lag 1 is important for predicting the current value after accounting for other lags.*
- *Subsequent lags do not show significant partial correlations.*

Methodology

Autocorrelation. An Autoregressive (AR) process is a type of stochastic time series model in which the current value of the series is based on the past values.

Based on these plots, an AR(1) model may be sufficient to model this time series data. Even when the lag=1 is barely significant in the figures, we could still use this.

- It is standard in the finance literature.

- Andrews, D.W.K. (1991), present a method for determining the correct number of lags using the model selection criteria. This method also suggests using only one lag.
    - *Information criteria balance model fit against model complexity (in this case, the number of lags) to select the most appropriate model.*
    - *There can be different criteria, but one of them is the Bayesian Information Criterion (BIC).*
    - *Testing out a 4-factor model with lag 1, with lag 2, ... until lag 20 and comparing the BICs of each model gives more clarity.*

Methodology

Autocorrelation. An Autoregressive (AR) process is a type of stochastic time series model in which the current value of the series is based on the past values.

Because of the correlation, we cannot use normal OLS estimators. We will use Newey-West estimators (1986) in our regression with the correct number of lags (p = 1) to correct for the time-dependency of returns in our dataset.

- Error terms are correlated over time. This violates the assumptions of ordinary least squared regression.
    - *Assumption of homoscedasticity: The error terms have constant variance (no heteroscedasticity).*
    - *Assumption of no autocorrelation: The error terms are not correlated with each other.*

- The Newey-West estimator can be used to improve the ordinary least squares regression. The abbreviation "HAC," sometimes used for the estimator, stands for "heteroskedasticity and autocorrelation consistent."

Methodology

Autocorrelation. An Autoregressive (AR) process is a type of stochastic time series model in which the current value of the series is based on the past values.

OLS estimates the parameters by minimizing the sum of the squared differences between the observed dependent variable and those predicted by the linear function. Mathematically, OLS solves:

(transposed) matrix of independent variables

vector of dependent variables

$$\beta = (X'X)^{-1}X'y$$

vector of estimated coefficients

The Newey-West estimator adjusts the standard errors of the OLS estimates to account for autocorrelation and heteroscedasticity. It does this by estimating a heteroscedasticity and autocorrelation consistent (HAC) covariance matrix. The Newey-West estimator is given by:

total time periods

vector of regressions for the t-th observation

lag truncation parameter, which is 1 in our case.

$$\hat{\Omega}_{\mathrm{NW}} = \sum_{t=1}^{T} \hat{u}_t^2 x_t x_t' + \sum_{l=1}^{L} w(l,L) \left(\sum_{t=l+1}^{T} \hat{u}_t \hat{u}_{t-l} (x_t x_{t-l}' + x_{t-l} x_t') \right)$$

residuals from the OLS regression

weighting function, typically given by the Barlett (1955) weight function

$$w(l,L) = 1 - \frac{l}{L+1}$$

Methodology

Autocorrelation. An Autoregressive (AR) process is a type of stochastic time series model in which the current value of the series is based on the past values.

Rewriting this for only one lag, specifying that L =1:

$$\hat{\Omega}_{\mathrm{NW}} = \sum_{t=1}^{T} \hat{u}_t^2 x_t x_t' + \sum_{l=1}^{1} w(l,1) \left(\sum_{t=l+1}^{T} \hat{u}_t \hat{u}_{t-l} (x_t x_{t-l}' + x_{t-l} x_t') \right)$$

$$\hat{\Omega}_{\mathrm{NW}} = \sum_{t=1}^{T} \hat{u}_t^2 x_t x_t' + w(1,1) \left(\sum_{t=2}^{T} \hat{u}_t \hat{u}_{t-1} (x_t x_{t-1}' + x_{t-1} x_t') \right)$$

Rewriting this for a Barlett weighting function: $w(1,1) = 1 - \frac{1}{1+1} = \frac{1}{2}$

$$\hat{\Omega}_{\mathrm{NW}} = \sum_{t=1}^{T} \hat{u}_t^2 x_t x_t' + \frac{1}{2} \left(\sum_{t=2}^{T} \hat{u}_t \hat{u}_{t-1} (x_t x_{t-1}' + x_{t-1} x_t') \right)$$

Methodology

Autocorrelation. An Autoregressive (AR) process is a type of stochastic time series model in which the current value of the series is based on the past values.

Example. Let's say we have the following observations to estimate a four-factor model.

$$R_{i,t} - R_{f,t} = \hat{\alpha}_i + \hat{\beta}_{i,market} * (R_{m,t} - R_{f,t}) + \hat{\beta}_{i,size} * SMB_t + \hat{\beta}_{i,value} * HML_t + \hat{\beta}_{i,momentum} * UMD_t + \epsilon_{i,t}$$

See file ExampleNW.xlsx.

Excess Portfolio Return and Comove Rank

(Cumulative) Average Return Excess over Time. We compare the average return of a portfolio minus the risk-free rate to get the excess return, similarly to the CAPM using the excess return as predicted variable.

Average Excess Return.

Average Return Excess over Time.

Cumulative Average Return Excess over Time.

Results of Robustness Tests: Alternative

alle technieken en mogelijke conclusies en vragen
ook zo hoe elke variable in berekend in detail, waar die van komt enzo en welke papers die meaning uitlegt - zie excel
!! wa was da me die ahumid illiquidity

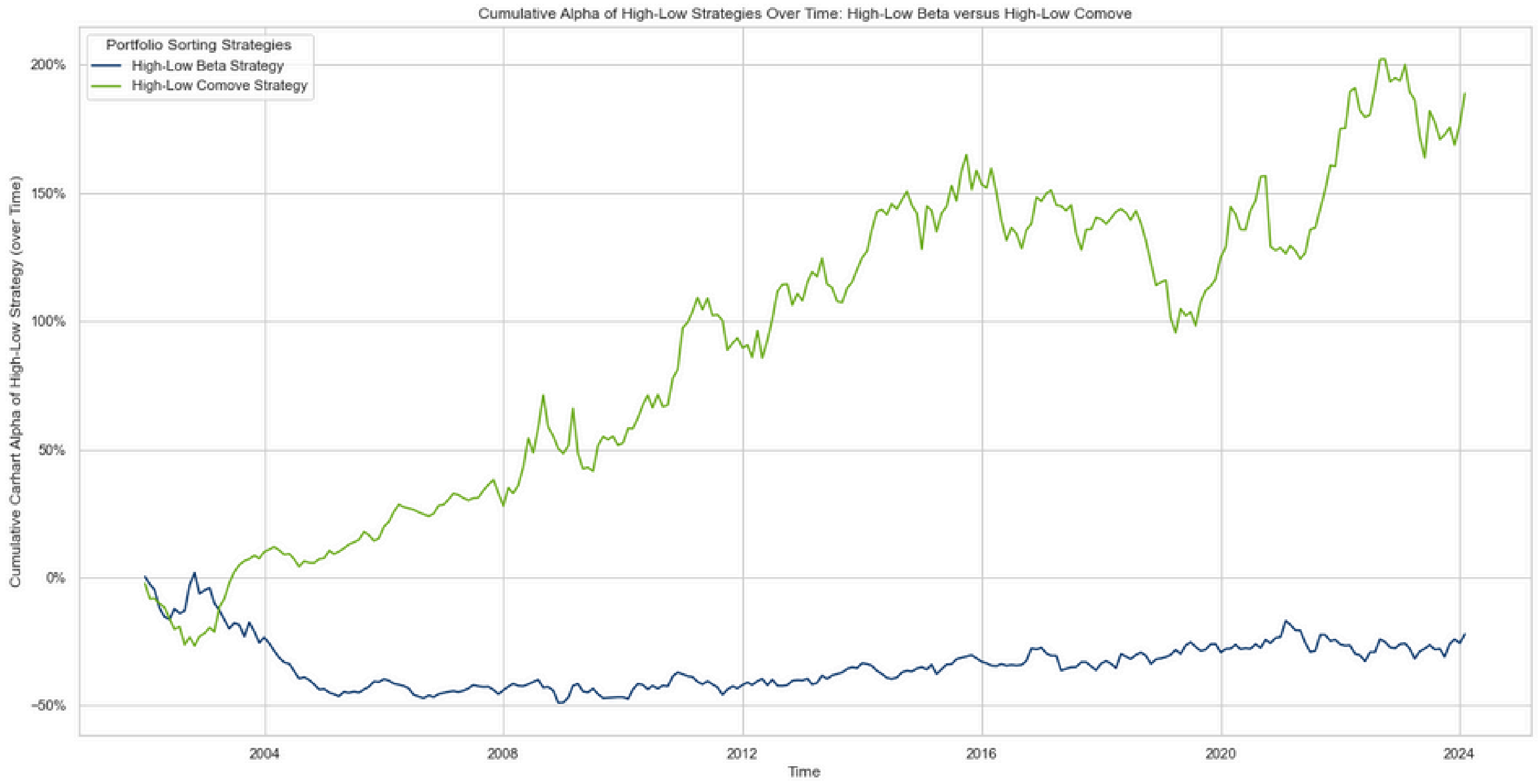
Key Insights

1 Beta and comovement are not the same.

High-low investment strategies show losses for portfolio's sorted on beta, while showing positive returns for portfolio's sorted on comovement.

The correlation between comovement and beta is negligible.

Contrary to the Capital Asset Pricing Model predictions and comovement, beta exhibited a significant negative coefficient in nearly all Fama and Macbeth regressions.



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

Key Insights

2 A comovement premium exists.

Annual outperformance of **6.05%** for portfolios with high versus low comovement frequency, which becomes significant after controlling for various factor models (from 6.77% to 10.59%).

Premium remains significant after considering alternative factor measures & asymmetric systematic, idiosyncratic, and liquidity risk with a premium of around 7% for the four-factor model. The premium is consistent in value-weighted portfolios, and when accounting for fixed effects.

High-Low Comove Strategy, Factor Models			
Newley-West	Jan 2002 - Feb 2024 *Yearly Comove Premium*	*Fama & MacBeth*	Jan 2002 – Feb 2024 *Yearly Comove Premium*
Raw	6.0539%	**4F**	7.0727% ***
CAPM	6.7651% ***	**4F + Asymmetric risk:** Upside and Downside Beta (Upper and Lower Tail Dep.)	8.6414% *** (7.4512% ***)
3F	7.4717% ***	**4F + Idiosyncratic risk** Idiosyncratic Volatility (Min and Max)	7.0072% *** (5.5717% **)
4F	5.4119% *	**4F + Trading Activity** Difference in & Absolute Ln(Turnover)	7.1019% ***
4F with value-weighted portfolio's	5.4135% *	**4F excluding small size, small price, and Londen Exchange**	7,0727% ***
5F	10.5857% ***	**5F**	18.3706% ***

Summary of some results of the main and robustness tests regarding the comove premium [Table 3, 6, 8, 9. and 10].

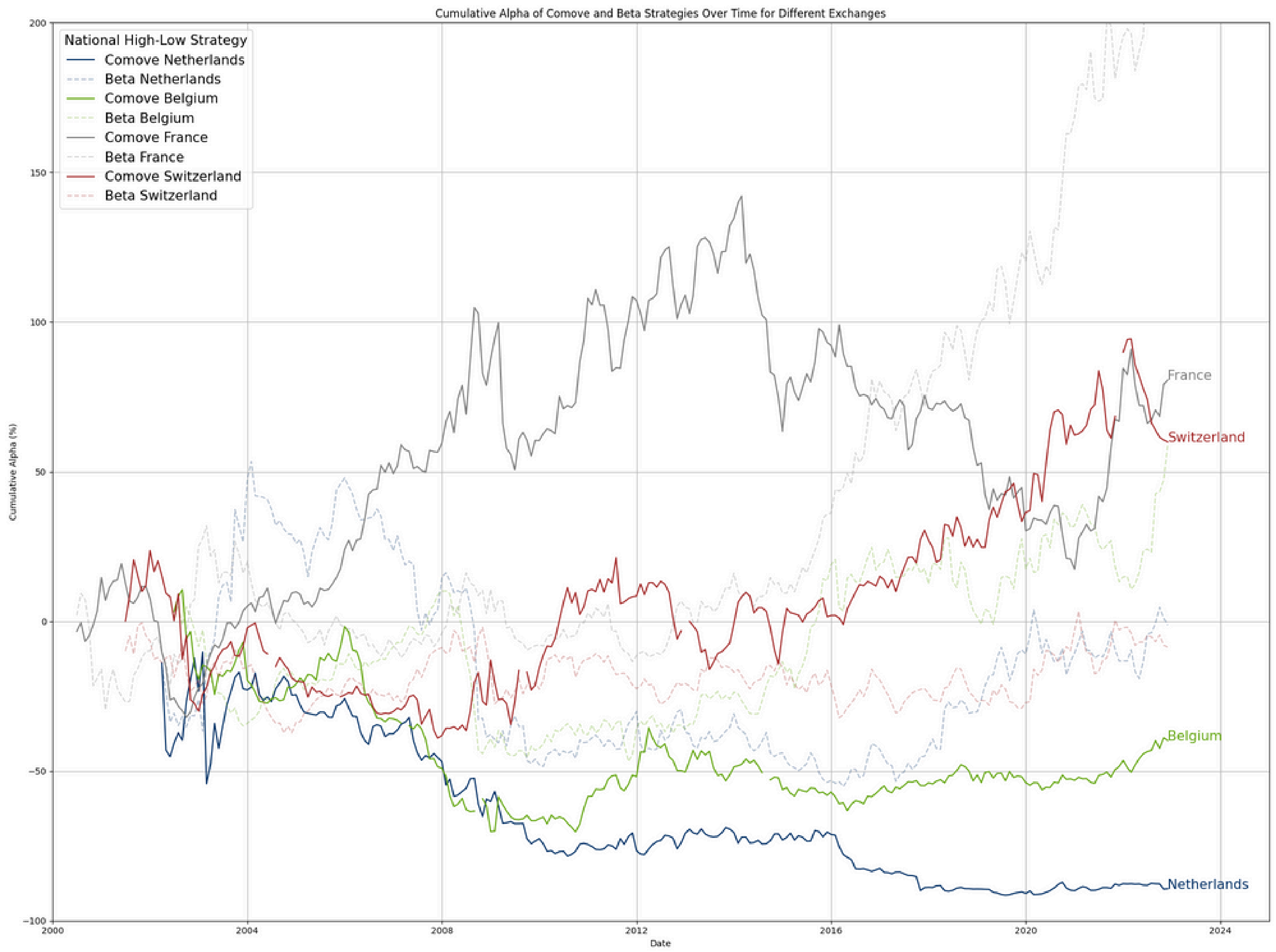
Key Insights

3 Methodological, geographical and temporal differences are observed.

Varying the methodology for measuring comovement impacts the return premium and its statistical significance.

The comovement premium appears slightly higher in Europe compared to the U.S., though results vary across European countries and are not consistently significant.

The comovement premium is more pronounced before 2015 and loses significance afterward.



Cumulative Carhart Alpha of High-Low portfolio over time: double-sorting on beta first and comove second (comove strategy, full) versus double-sorting on comove first and beta second (beta strategy, transparent) in Belgium (BEL20, green), France (CAC40, grey), the Netherlands (AMX, blue), and Switzerland (SMI, red) [Figure 8].

Future Research

Geographical & temporal trends

Given the decline post-2015 and differences in American versus European markets, as well as within markets, further research is warranted. Does market (risk) move in the same patterns?

Understanding & use of measures

Do people genuinely not understand correlation, or do find it cognitively easier to use a simple counting heuristic? What do both measures mean and why is there a different impact on stock returns? Better predictor?

Applicability

Using other indexes, different factor models, data before 2000, macroeconomic factors and different asset classes may enhance the applicability of the findings. The relationship between comovement and momentum deserves detailed exploration.

Extra

Hier nog iets over future research?
ook nog is goe nalezen, nog extra vragen die je kan bedenken die erin meoten? effe mama en papa laten lezen?

bad factor data -> ook een reden waarom predicting moeilijk was
bv bij market premium in alle factor modellen bijna negatief coefficient, tegenstelling tot capm -> moeilijk om te testen
also this beta estimated coeff not close to one in estimations main results, but when avg beta in fama and macbeth it is 0.9915

Thank You

More information and code can be found on my Github account:

Luna's Github

References

Introduction and anomalies of the Capital Asset Pricing Model

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

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

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

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *The Journal of Finance, 1*9(3), 425–442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

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

a. Factor models

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

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

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

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. (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

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

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

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

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

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

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

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

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

References (cont.)

b. Unrealistic assumptions

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

Baker, M., & Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance, 6*1(4), 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

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

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

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

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

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

c. Empirical testing difficulties

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

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.

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

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

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

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

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

Correlation, Return, and Perceived Dependence

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

References (cont.)

Methodology

a. Techniques

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

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

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

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

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

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

b. Meaning and Data Sources of Additional Variables

The variables beta, frequency of comovement, and return of portfolios are from retrieved DataStream software and based on the return index of the STOXX Return 600 index.

b1. Main Results

For market premium, SMB, HML, RMW, and CMA: 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

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

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

For carry and seasonal: 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

b2. Additional Factor Measures

For market premium_EUR50: The market rate is retrieved from DataStream software and based on the return index of the STOXX Return 600 index. The risk-free rate is retrieved from DataStream software and based on the return index of the EONIA and Euro-Short Term Rate.

References (cont.)

For HML_Devil: AQR Capital Management. (2024a). *Betting Against Beta: Equity Factors Data, Monthly* [dataset]. https://www.aqr.com/Insights/Datasets/Betting-Against-Beta-Equity-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
For UMD_Trend: 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
Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2011). *Time Series Momentum* (SSRN Scholarly Paper 2089463). https://doi.org/10.2139/ssrn.2089463

b3. Additional Index

The variables beta, frequency of comovement, and return of portfolios are from retrieved DataStream software and based on the return index of the AMX (Netherlands), BEL20 (Belgium), CAC40 (France), DAX (Germany), OMX (Sweden), and SMI (Switzerland) index.

b4. Alternative Portfolio Aggregation

The variables beta, frequency of comovement, and return of portfolios are from retrieved DataStream software and based on the return index of the STOXX Return 600 index, but were calculated differently.

b5. Controlling with Fama and MacBeth Regressions

All additional data needed for the calculation of these variables is retrieved from DataStream.

For other measurements of dependency and volatility: 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
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
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
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
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
Gumbel, E. J. (2019). Statistics of Extremes. In *Statistics of Extremes*. Columbia University Press. https://doi.org/10.7312/gumb92958

References (cont.)

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

For other benchmarks, fixed effects and skipped month: 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

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

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.

For varying the comove measure and the sample: not applicable.

Contribution to literature and SDGs

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

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.

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

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

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

Suggestions for future research

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

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

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

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