PERCEIVED MARKET DEPENDENCE AND ITS EFFECT ON STOCK RETURNS

When Harry Markowitz introduced his Modern Portfolio Theory (1952), he elevated a familiar proverb—*don't put all your eggs in one basket*—into a cornerstone of modern investing. By spreading money across different stocks, investors can smooth out the bumps that come from individual companies' ups and downs. Diversification helps to eliminate what is known as unsystematic risk—risks specific to a single firm. For example, the UK retailer WH Smith's shares plunged by nearly 40 percent this morning, after the company revealed a £30 million accounting error (Moreau, 2025). For an investor holding only WH Smith, such a loss would be devastating. But within a well-diversified portfolio, the blow is softened, as positive or stable returns from other assets help to offset the decline.

What investors cannot escape, however, is systematic risk: the broader forces that affect markets as a whole, such as economic recessions, rising interest rates, or geopolitical crises. The global financial crisis of 2008 demonstrated this clearly, when returns on almost all emerging equity markets experienced steep declines (Dimitriou et al., 2013).

TO BETA OR NOT TO BETA… THAT IS THE QUESTION.

A decade later, William Sharpe built on Markowitz's work with his Capital Asset Pricing Model (Sharpe, 1964). Sharpe's insight was blunt: investors only get paid for the risks they cannot avoid.

Higher Beta Means Higher Return

Since diversification removes company-specific risks, the return an investor can expect from a stock depends solely on its exposure to systematic risk—the extent to which it moves with the market as a whole. In other words, the CAPM shows that a stock's expected return is directly proportional to its market risk alone. The CAPM formula, $E(R_i) = R_f + \beta_i * (E(R_m) - R_f)$, illustrates this relationship. In this equation,

- $E(R_i)$ is the expected return of a stock.
- R_f is the risk-free rate and is typically represented by government bond yield.
- $E(R_m)$ is the expected return of the overall market, often proxied by broad stock indices.
- The key variable, β_i (beta), captures how sensitive a stock is to market movements.

In the past and common practice, researchers have used correlation between historical stock and market returns as a proxy for beta. A high-beta stock, such as Tesla, amplifies the market's mood: when the market rises 10%, Tesla might jump 15%, but it can also sink more sharply in a downturn. Low-beta stocks, like those in the utility sector, are steadier; they rise less in good times but also cushion losses in bad ones. According to CAPM, higher-beta stocks should reward investors with higher expected returns to make up for greater exposure to market-wide risk.

I Got 99 Problems… And Beta is Definitely One

Despite its popularity, empirical research has questioned the validity of beta in the CAPM. The first major critique is that market risk alone fails to fully explain expected returns. Fama and French (2003) showed that some stocks earn higher returns than CAPM would predict, while others earn less—even if they have the same beta. For example, small companies often deliver better long-term returns than large ones, and "value stocks" (companies that look cheap given their main KPIs) often outperform "growth stocks." CAPM can't account for these patterns.

This led to the development of multifactor models, which add extra dimensions of risk beyond just beta. For example, Fama and French (2003) introduced their three-factor model, adding company size and value as key drivers of returns. They later expanded this to a five-factor model (2015), also including profitability and investment decisions. Similarly, Mark Carhart (1997) added a fourth factor, momentum—the idea that stocks that have gone up recently tend to keep rising in the short run. The literature provides additional examples (Asness et al., 2015; Frazzini & Pedersen, 2014; Kelly & Jiang, 2014; Keloharju et al., 2016; Koijen et al., 2016; Pastor & Stambaugh, 2001; Sadka, 2003).

A second major line of criticism targets the assumptions behind CAPM, which many argue are too simple to reflect reality (Blitz et al., 2013). Take the idea of a "risk-free asset." According to the model, investors should be able to lend or borrow unlimited amounts at a guaranteed rate without risk. The problem? No such thing exists. Even government bonds—the textbook example of "risk-free"—come with risks, and their yields rise and fall with the economic tide (DeJong & Collins, 1985). The risk-free rate also differs between borrowing and lending (Black, 1972; Friend & Blume, 1970): the rate you pay the bank for borrowing money is almost never the same as the rate you'd earn by lending.

Then there's the elusive "market portfolio." In theory, it should include every asset in the world—stocks, bonds, real estate, commodities, even your neighbor' Pokémon cards collection. In reality, no one can observe or hold such a portfolio (Roll, 1977). So researchers fall back on stock indexes like the S&P 500 as a proxy, knowing it's only a rough approximation. Further critiques on CAPM assumptions appear in the literature (Aghion et al., 2003; Constantinides, 1986; Merton, 1973; Pastor & Stambaugh, 2001; Reilly & Brown, 2011).

A third challenge for CAPM is that it's tricky to test in the real world. The model leans heavily on beta—a number that's supposed to measure how much a stock moves with the market. The problem? Beta won't sit still. Studies show it changes over time (Blume, 1971, 1975; Ferson & Harvey, 1991; Jagannathan & Wang, 1996). A stock that looks risky one year might look much tamer the next, which makes prediction messy.

Another reason why beta doesn't always predict stock prices correctly is that investors may not pay as much attention to market risk as the model assumes. Maybe investors don't care as much about market risk of a stock than we think they do. This idea is known as correlation neglect—the tendency for investors to overlook how closely a stock's return moves with the market (Enke & Zimmermann, 2013; Eyster & Weizsacker, 2016).

However, more recent research shows that the issue is not merely that investors ignore correlation, but that they perceive market dependency differently. Whereas economists typically use historical return correlations to estimate beta, investors rely on intuitive judgments shaped by their own perceptions (Laudenbach et al., 2019; Ungeheuer & Weber, 2020). Put simply: investors *do* care about how much a stock moves with the market, but they don't always see that connection in the same way correlation suggests. This discrepancy can explain why CAPM's predictions often fail in practice: not because the model is inherently flawed, but because investors interpret risk in ways that deviate from the statistical assumptions of the model (Bossaerts & Plott, 2004).

THE FREQUENCY OF COMOVEMENT

Ungeheuer and Weber (2020) looked at how people actually judge the link between stocks (or, in the CAPM, a stock and the overall market). Economists typically measure this relationship using correlation, which captures how strongly two assets move together. Importantly, correlation takes into account all return magnitudes, from minor daily fluctuations to large market swings. As a result, it heavily weights extreme events.

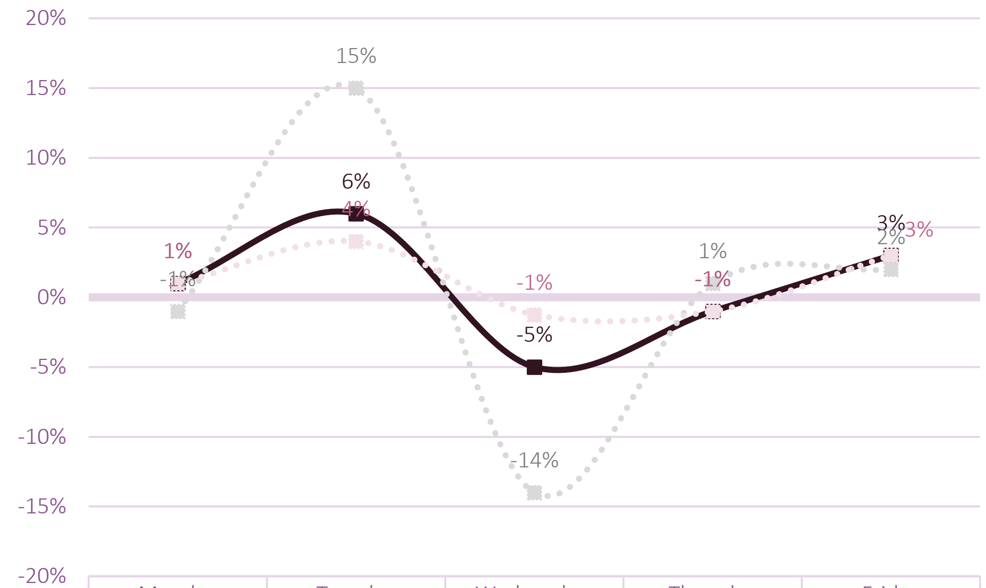
How Do Investors Perceive Market Dependency?

However, Ungeheuer and Weber (2020) found that investors do not naturally think in terms of correlation. Instead, they appear to rely on a simpler mental model. The researchers proposed a new measure: frequency of comovement. Unlike correlation, which considers the magnitude of co-movements, frequency of comovement focuses solely on how often a stock and the market move in the same direction—regardless of the size of those movements. This method places less emphasis on rare, extreme returns and more on the frequency of directional alignment.

Why might this be a more accurate reflection of how investors think? Empirical results show that people are relatively good at detecting patterns in moderate, day-to-day returns but tend to struggle with interpreting extreme price changes. When forming expectations about overall dependence, investors tend to rely more on consistent, moderate co-movements and overlook the impact of rare, volatile days. In short, rather than calculating correlation, investors seem to use a kind of "counting shortcut"—simply noticing how often stocks rise or fall together—rather than doing complex statistical math like correlation.

Let me explain this with a fictive example. Lets proxy the market return with an index such as the S&P 500. Let's look at its return in the past few days. The average weekly return of the market was 0.80% this week. It had a few extreme returns (6% on Tuesday and -5% on Wednesday) and a few more moderate returns (1% on Monday, -1% on Thursday and 3% on Friday).

Let's now take two stocks, Tesla and NVIDIA, and their returns in the past five days. Note that if you would calculate the correlation between the market returns and the stock returns, both would have a correlation close to 94%. In other words, both stocks have the same beta. Since they have similar market risk, the CAPM predicts that they would have similar returns. However, the observed returns diverge: Tesla underperforms with a market premium of –0.20%, while NVIDIA outperforms with a premium of +0.35%. This discrepancy illustrates a potential failure of CAPM predictions when market risk is measured solely by correlation.



	Monday	Tuesday	Wednesday	Thursday	Friday
S&P 500 Return	1%	6%	-5%	-1%	3%
Tesla Return	-1%	15%	-14%	1%	2%
NVIDIA Return	1%	4%	-1%	-1%	3%

To investigate why the predictions of the CAPM do not hold in this case, Ungeheuer and Weber (2020) examined how investors perceive the relationship between individual stocks and the market. Statistically, both Tesla and NVIDIA have the same correlation with the market, suggesting identical market dependency. However, the researchers' survey results revealed that investor perceptions differ significantly from this statistical equivalence.

Participants were asked to evaluate three dimensions of market dependency: overall dependence, dependence during periods of extreme market returns, and dependence during periods of moderate market returns. When focusing on the extreme days—Tuesday and Wednesday—the market experienced large movements of +6% and

–5%. On these days, Tesla showed strong alignment with the market, returning +15% and –14%, respectively. This suggests that Tesla has a high sensitivity to extreme market movements. NVIDIA also moved in the same direction, but less dramatically, with returns of +5% and –4%. Therefore, in terms of extreme returns, Tesla appears more dependent on the market than NVIDIA. However, the study demonstrated that most investors do not intuitively understand or give much weight to these types of extreme co-movements.

Attention then shifted to the remaining days—Monday, Thursday, and Friday—when market movements were more moderate, with returns of +1%, –1%, and +3%. During these days, Tesla's returns followed the market to some extent but with noticeable deviations. NVIDIA, in contrast, mirrored the market precisely on each of these days. This indicates that, in the context of moderate returns, NVIDIA is perceived to have stronger market dependency than Tesla.

Finally, when investors were asked to assess the overall market dependence of the two stocks, the results aligned with their views on moderate-day co-movements. Even when they were able to correctly identify Tesla's stronger response to extreme returns, investors consistently judged NVIDIA to be more closely tied to the market overall. This finding supports the central claim of Ungeheuer and Weber (2020): investors place disproportionate weight on frequent, moderate comovements when assessing market risk, effectively ignoring or downplaying the impact of rare, extreme events.

How Can We Measure Perceived Market Dependency?

This raises the question: how should market dependency be measured? While both Tesla and NVIDIA exhibit the same correlation with the market, Ungeheuer and Weber (2020) argue that correlation is not an adequate measure of perceived dependency. Correlation captures both the direction and magnitude of return co-movements, but investors appear to focus primarily on the direction of movement—particularly in moderate return scenarios. As an alternative, the authors propose the frequency of comovement, which simply counts the proportion of days in which a stock's return has the same sign (positive or negative) as the market return. This measure aligns more closely with how investors intuitively assess risk, since it underweights extreme deviations and emphasizes consistency in direction.

Applied to the earlier example, Tesla shares the same return sign with the market on three out of five days, resulting in a frequency of comovement of 60%. NVIDIA, on the other hand, matches the market's return direction on all five days, yielding a frequency of 100%. Based on this measure, investors perceive NVIDIA to be more strongly tied to the market, and therefore more exposed to systematic risk. Consequently, NVIDIA earns a higher return than Tesla, even though both stocks have identical betas. This supports the idea that discrepancies between CAPM predictions and actual returns may stem from the model's reliance on correlation, rather than on the simpler heuristics investors tend to use.

THE FREQUENCY OF COMOVEMENT & ITS EFFECT ON STOCK RETURNS

In more fancy words, Ungeheuer and Weber's (2020) findings indicate that stocks with a higher frequency of comovement are perceived as having greater market risk, which translates into a higher return premium.

Why Comovement Might Matter More Than Beta

To put their theory to the test, they analyzed U.S. stocks listed on the NYSE, AMEX, and NASDAQ between 1963 and 2015. Their approach was straightforward but powerful. They divided the stock universe into groups based on how often each stock's return moved in the same direction as the overall market. Every month, they would "go long" (buy) the stocks with the highest frequency of comovement, and "go short" (sell) those with the lowest. If the market truly priced comovement as a form of risk, then stocks that more frequently moved in sync with the market should earn higher returns to compensate investors for bearing that perceived risk.

The results were striking. This strategy delivered an average annual return premium of 4.28%, and crucially, this excess return persisted even after controlling for traditional risk factors—including beta, size, value, and momentum. This means the performance could not simply be explained by known factors already included in established models like the CAPM or Fama-French. In technical terms, the comovement premium was alpha—additional return not captured by existing models.

What does this tell us? Essentially, stocks that frequently mimic the market's ups and downs are interpreted by investors as being more exposed to systematic risk—even if their statistical beta suggests otherwise. And because riskier stocks are expected to offer higher returns, these high-comovement stocks get priced with a return premium. The market is not rewarding them because they *move more* with the market (as beta measures), but because they *move more often* in the same direction—a subtle, yet crucial distinction.

Europe Tells a Similar Story

Inspired by the U.S. findings, this thesis set out to explore a natural next question: Does the same pattern hold in Europe? If stocks that frequently move in the same direction as the market are rewarded with higher returns in the U.S., would European investors behave the same way?

To find out, a large-scale analysis was conducted using stock data from the STOXX Europe 600 index, which covers major companies across 17 European countries. The study looked at monthly stock and market returns over a span of 22 years, from January 2002 to February 2024—a period that includes both financial crises and bull markets. Just like in the original U.S. study, each stock in the index was measured by two key metrics: its beta, and its frequency of comovement with the market. To isolate the effect of comovement on returns, stocks were grouped into five comovement quintiles, and within each comovement group, beta was allowed to vary. This sorting resulted in five portfolios per month, each containing stocks with similar levels of comovement but differing beta values.

The returns of these portfolios were then analyzed using the CAPM and multi-factor models, allowing the study to test whether comovement frequency has explanatory power for stock returns beyond what beta can capture. Newey-West estimators (1986), adjusted for a single lag, correct for time-dependency in the returns. At first glance, the raw return difference between these portfolios was modest: only 0.50% per month, and not statistically significant.

But things got more interesting once traditional risk factors were taken into account. Using the Carhart Four-Factor Model—a widely accepted method for adjusting returns for market, size, value, and momentum effects—the return premium for high comovement stocks jumped to a statistically significant 5.41% per year. And it didn't stop there. When more advanced models, such as the Fama-French 3- and 5-Factor Models, were applied, the return premium was even larger—ranging between 6.77% and 10.59% annually. These results were especially strong in the earlier years of the sample, suggesting that the comovement premium may have been even more pronounced during periods of market stress or uncertainty.

To test the robustness of these findings, a wide range of additional checks were performed. The analysis was repeated using different ways of calculating comovement, alternative market indices, and both equal- and value-weighted portfolio constructions. Even when running Fama-MacBeth regressions—a gold standard for analyzing cross-sectional return predictors—the comovement effect mostly held up. Only a few variations showed weaker or insignificant results.

Comovement vs. Beta

However, what's particularly striking is that comovement and beta appear to be almost unrelated in the European data. The correlation between the two is just 0.01, which is essentially zero. This means that stocks that frequently move in the same direction as the market do not necessarily have high betas, and vice versa. In other words, comovement captures a different dimension of market risk—one that is not reflected in traditional beta-based models like the CAPM.

The return patterns also tell an interesting story. Investment strategies that buy high-comovement stocks and sell low-comovement stocks yielded positive and consistent cumulative returns. In contrast, strategies based on beta—buying high-beta stocks and selling low-beta ones—actually produced negative returns. This is a direct contradiction to what the CAPM predicts, which is that higher-beta stocks should earn higher returns as compensation for higher market risk. Further evidence comes from Fama-MacBeth regressions, a method used to evaluate the impact of different risk factors on returns over time. In these regressions, beta consistently had a significant negative coefficient, meaning that higher-beta stocks tended to earn lower—not higher—returns. These findings highlight comovement frequency as a distinct and valuable factor in portfolio construction and risk assessment, complementing or replacing traditional beta measures.

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This is a journalistic summary of the thesis "Perceived market dependence and its effect on stock returns: An empirical analysis of European markets" written by Luna Geens under supervision of Prof. dr. Jan Annaert. It is written in August 2025, more than a year after the thesis was finished. The full thesis can be found on Github.

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Appendix

Table 1 - Fictive Example

Day	Variable	Monday	Tuesday	Wednesday	Thursday	Friday
Market	S&P 500 Return	1%	**6%**	**-5%**	-1%	3%
	Average Return			*0,80%*		
Stock A	Tesla Return	-1%	**15%**	**-14%**	1%	2%
	Correlation (beta)			*94%*		
	Same Sign?	*0*	*1*	*1*	*0*	*1*
	Frequency of Comovement			*60%*		
	Average Return			*0,60%*		
	Return Premium			*-0,20%*		
Stock B	NVIDIA Return	1%	**4,0%**	**-1%**	-1%	3,0%
	Correlation (beta)			*94%*		
	Same Sign?	*1*	*1*	*1*	*1*	*1*
	Frequency of Comovement			*100%*		
	Average Return			*1,15%*		
	Return Premium			*0,35%*		