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"The Fama-French Three-Factor Model and financial leverage in The Netherlands"

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ABSTRACT

Numerous financial empirical studies show that the size effect (SMB) and the value effect (HML) of the Fama & French (1992) Three-Factor Model do not fully capture financial leverage or default risk. To explore this, we augment the Fama & French Three-Factor Model with financial leverage (Debt/Assets) as an additional risk factor (High-Leverage-Minus-Low-Leverage). This creates the Four-Factor Model whose performance is then compared to the Three-Factor Model. Our findings suggests that financial leverage is not significant in explaining Dutch stock returns and the Four-Factor Model does not outperform the neither the CAPM nor the Three-Factor Model in the daily data. The monthly Four-Factor Model outperforms only the CAPM Model and not the Three-Factor Model.

Keywords: Three-Factor Model, SMB, HML, financial leverage, asset pricing

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1. Introduction

Fama & French (1992) proposed the Three-Factor Model by arguing that out of five potential risk factors (i.e.: market ß, size, B/M[1], financial leverage, and E/P[2]), size and value are the best proxies at explaining stock returns. They prove that the size factor (SMB)[3] and the value factor (HML)[4], absorb the role of both E/P and financial leverage. However, subsequent studies show that the SMB and HML factors do not capture default risk and that the priced risk that they capture remains an open question (Griffin & Lemmon, 2002). Additionally, several studies find that default risk seems to be a significant firm characteristic that seems to be priced into the cross-variations of equity returns (Vassalou & Xing, 2004).
Its prominence and impact are supposed to be seen on higher required equity returns, implicitly rewarding investor to compensate for the company's financial distress that it bears. The finding further suggests that default risk should be considered as systematic risk, also known as market related risk, that cannot be diversified away. On the contrary, a lot of other studies suggest that default risk could potentially reflect the idiosyncratic risk of a particular company (Fiordelisi & Marqués-Ibañez, 2013). In a nutshell, there is no clear consistent evidence of how default risk impacts the volatility of stock returns, indicating that it could be a potential asset pricing anomaly that requires further investigation.

Furthermore, various studies express leverage through different ratios, adding to the ambiguity and inconsistency of how leverage affects stock prices. In this paper, we choose to investigate financial leverage, represented by total debt/total assets (D/A). Hence, the research question explores the significance of financial leverage in Dutch equity excess returns. This is followed up by a model comparison between the Fama & French Three-Factor Model and the Four-Factor Model which includes financial leverage as its fourth factor. We use the multi-factor model regressions and methodology from (Fama & French, 1992, 2015). The AEX index is chosen as the sampling representative of the Dutch stock market in The

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[1]Book/Market is a ratio that compares the fundamental accounting book value of the firm relative to the market value of the firm.
[2] Earnings/Price is a ratio that measures the firm's earnings-per-share (EPS) relative to its current share price.
[3] SMB refers to small-cap firms minus big-cap firms. Its computation is explained in detail in Section 5.3.2.
[4] HML refers to high-valued firms minus low-valued firms. Its computation is explained in detail in Section 5.3.2.

Netherlands. The goal of this research is to provide further insight of how financial leverage affects stock prices in a European framework.

Lastly, the structure of the paper is as follows: Section 2 is literature review which aims to encapsulate the economic theory behind the topic of the central research question. We introduce the first existing prominent factors out there that are fundamental to asset pricing. This part establishes the current multi-factor models. It further depicts the emergence of the size and value effect and how they came to be. We then follow up discussing other empirical literature that contradict their relevance and challenge their ability to subsume the role of financial leverage. This brings us to Section 3 of hypotheses formulation that posits the significance of financial leverage in explaining Dutch stock returns. Section 4 follows with the description of the raw data source and the collection procedure. Section 5 is methodology which explains the formulation of the Four-Factor Model, portfolio sorting, factor formation, descriptive statistics and the analytical techniques used to conduct the regressions. Section 6 presents regression results and compares the CAPM, the Three-Factor Model and the Four-Factor Model with regards to their performance and predictive abilities. Section 6 also discusses and interprets results. Finally, Section 7 summarizes our findings by identifying the limitations of our research and recommending improvements for future research.

2. Literature Review

2.1 Important Fama-French factors

In asset pricing and portfolio management, the Fama-French Three-Factor Model expands on the capital asset pricing model (CAPM) by adding two additional risk factors: size and value effect.

The CAPM model is the fundamental asset pricing model in finance which investigates the relationship between systematic risk and expected return (Lintner, 1965; Sharpe, 1964). The goal of CAPM is to show that all stock returns can be explained by a single factor, the non-diversifiable market systematic risk (ß), after accounting for the risk-free rate, equation 1.

$$E(R_i) = r_f + \beta_i \left(E(R_m) + r_f\right) \quad (\mathbf{1})$$

$E(R_i)$ represents the expected return on stock *i.* r_f represents the risk-free rate. $E(R_m)$ represents the expected return on the market portfolio and β_i measures the stock *i* volatility with regards to the market risk premium. This positive relationship between stock returns and market risk suggests that the higher the non-diversifiable market risk, the higher the expected stock return. Hence, the idea is to show the amount of compensation equity investors need for taking additional risk (Mcclure, n.d.).

Despite boundless use, CAPM still to this day is criticized for its vagueness when it comes to predicting stock returns. The stability of beta being the key weakness. In practice, CAPM beta is estimated from historical returns resulting in a historical beta. This makes it questionable if historical beta can be used as a future beta estimate (Mirza & Shabbir, 2005). Other researchers, like Blume & Husic (1973) showed that betas are not stable over time. Moreover, Fama & French (1992) indicate no reliable relationship between beta and average returns.

Next, Fama & French (1992) further explore if other factors could potentially explain stock returns. The research essentially finds that factors like size, value, leverage, and earnings-to-price (E/P), seem to strongly correlate with average stock returns. The size factor suggests that smaller companies outperform bigger ones. The argument lies on the fact that a smaller cap firm can grow much faster and is riskier than a larger one (Hayes, n.d.). It is also calculated as small-minus-big (SMB). The value factor suggests that high book-to-market

(B/M) companies will have higher expected returns than low book-to-market companies. The reason being that undervalued companies trade at a lower price relative to their fundamental value, suggesting long-term prospect and growth. A higher B/M signals undervaluation because the market values it less than the company's true fundamental book value. Undervalued stocks are also known as value stocks currently trading at a lower price than their true value. Overall, they're considered as larger and more established companies that are expected to carry lower risk in the long-term (Cussen, n.d.). On the contrary, a lower B/M signals overvaluation because now the market values the company more than it should. Overvalued stocks are also known as growth stocks. They focus on expansion and investing opportunities which makes them face a higher risk but also a higher potential return for investors. This ratio helps in computing the value factor high-minus-low (HML). The next factor is leverage. Fama & French (1992) consider both market leverage
(Assets/Market Value) and book leverage (Assets/Book Value) which turn out to predict returns oppositely. Nonetheless, this is adjusted by taking the log difference which conveniently equates into the B/M ratio [ln(B/M) = ln(A/M) – ln(A/B)]. According to Fama & French (1992), the close link between the B/M value and leverage suggests that leverage is only a different method to interpret the value effect. Lastly, E/P serves as a proxy for all unspecified factors that affect the expected returns (Ball, 1992). E/P is likely to be greater for companies with larger risks and projected returns, irrespective of the uncertainty of the unspecified risk.

Nonetheless, due to reasons of parsimony, Fama & French (1992) decided to formulate their Three-Factor Model including only the size and the value factor since those two factors absorb the roles of leverage and E/P on average, equation 2.

$$R_{it} - r_f = \alpha + \beta_i \left(R_m - r_f\right) + s_i SMB + h_i HML + e_{it} \quad (\mathbf{2})$$

In equation 2, $(R_{it} - r_f)$ represents the risk-free return of stock *i* in time *t*. α represents the intercept of the regression. $\beta_i \left(R_m - r_f\right)$ represents the risk-free market return like in CAPM, equation 1. $s_i SMB$ represents the size factor which implies a negative relationship between size and abnormal returns. $h_i HML$ represents the value factor implying a positive relationship between a B/M ratio and abnormal returns. e_{it}represents idiosyncratic risk, whose expected value is assumed to be zero.

Finally, as per equation 2, Fama & French (1992) conclude that the three main important factors are: market premium, size factor, and value factor. Consequently, at the time, the Three-Factor Model became the new fundamental factor model that overtakes CAPM due to its outperformance in stock pricing prediction.

2.2 Objections to SMB & HML

As previously explained, the size and value effect are assumed to proxy for financial leverage and price default risk by a vast number of researchers. Research by Liew & Vassalou (2000) and Hussain et al., (2002) confirm the use of B/M as a measure of financial distress risk and suggest that the value effect is a feature of bankrupt business entities. However, in the recent years, various studies started to find conflicting findings with those of Fama & French (1992). This raises a key asset pricing concern about the precise risk that SMB and HML capture, as well as whether they can subsume the role of financial leverage in equity research.

Vassalou & Xing (2004) appears to be one of the first studies to explore the impact of default. The study finds that both the size and value factors seem to be correlated with the default effect because they both factors happen to occur when default risk is high. This suggests that firms with high default risk earn higher returns only for as long as they are characterized as small and undervalued. However, Vassalou & Xing (2004) conclude that the reason why SMB and HML factors can explain returns is completely unrelated to default risk. This further implies that default risk is not properly proxied by SMB and HML, hence its impact cannot be fully observed through the Three-Factor Model. Similarly, Griffin & Lemmon (2002) study shows that SMB and HML appear significant only in high default risk firms. The findings also further conclude that the value effect could be significant because of mispricing error.

A study by Gharghori et al. (2007) investigates whether SMB and HML proxy for default risk in the Australian market. The findings show these two factors as significant, nonetheless, they still do not proxy for default risk. A study conducted by Boubaker et al. (2018) similarly contributes to the above-mentioned literature that the size and value factors are insufficient factors to explain the effect of leverage in equity returns.

Moreover, Campbell et al. (2008) also finds that the SMB and HML factors do not account for financial distress. Similar conclusion is also reached by (Mirza et al., 2013).

Following all these opposing findings, it remains unclear and an open question how financial leverage or default risk affect equity returns precisely.

2.3 Default risk as a systematic factor

The next point of contention is whether default risk is systematic or idiosyncratic. Systematic risk refers to market risk that can never be fully diversified away, hence undiversifiable risk (Chen, n.d.). Idiosyncratic risk, on the other hand, refers to firm-specific risk that may be entirely reduced through diversification.

Default risk and financial distress both occur in the event of the firm's inability to pay its debt obligations (Fiordelisi & Marqués-Ibañez, 2013). In that respect, investors are indirectly promised a larger return to compensate for the level of risk they take. According to this rationale, firms with a larger risk of default should have their equity returns priced higher as well. Modern portfolio theory introduced by Markowitz (1952) suggests that equity premium is usually a result of systematic risk. Similarly, show that when a single bank fails, the default risk spreads to mostly all the other institutions. This rise in overall financial risk, which cannot be mitigated, is unavoidable.

On the contrary, Levy (1978) demonstrated that idiosyncratic risk can only explain the stock premium under the assumption of under-diversified portfolios. However, diversification is a relatively straightforward process in portfolio management, implying that most of the time, default risk may be classified as systematic risk. Besides that, systematic risk is linked to the systemic nature of banking. That is, there are financial institutions whose bankruptcy may spark off a chain reaction of negative consequences. In such circumstances, the collapse of one of these institutions has a significant impact on the stock market values of many other banks (Fiordelisi & Marqués-Ibañez, 2013).

2.4 Augmented Fama & French Three-Factor Model

Once we establish that default risk is primarily systematic risk, we may price it in terms of cross-sectional return variation and so properly examine it. There are different ways how you can choose to represent financial distress that companies face. The research done by

Vassalou & Xing (2004) estimates default likelihood indicators (DLI) as functions of default probabilities for individual firms. Penman et al. (2007) mentions that default probability or bankruptcy risk can be measured through the Altman (1968) Z-score or Ohlson (1980) O-score.

An empirical study by Muradoglu & Sivaprasad (2008) defines leverage as the debt-to-equity ratio (D/E). Lastly, Mirza et al. (2013) calculate a leverage premium factor by taking the difference of portfolios that consist of high-levered firms and those that consist of low-levered firms. As we can see, leverage is represented and measured differently in each study. However, as several studies suggest, the best strategy to investigate the impact of financial leverage is to include it as an additional risk factor to the Fama & French (1992) Three-Factor Model. In our paper, the leverage factor will represent the leverage ratio of a firm, the total amount of debt relative to total assets owned by the firm total debt/total assets (D/A). This ratio indicates the extent of shareholder's equity to sustain the creditors' obligations in the event of bankruptcy. The higher the D/A, the more leverage a firm has, hence the higher its bankruptcy risk. The inclusion of the leverage factor will augment the Three-Factor Model into a Four-Factor Model.

3. Research hypotheses

Overall, the goal is to see how important leverage is in explaining equity returns, as well as if the Four-Factor Model outperforms the Three-Factor Model and CAPM. The ambiguity of financial leverage in equity research leads us to the proposition of the following hypotheses.

3.1 Hypothesis I: *Financial leverage will have a positive effect on stock returns, suggesting that highly levered firms will yield higher returns than low levered firms.*

Financial leverage will be an additional risk factor added to the Three-Factor Model to check if it's a significant factor in explaining variations in cross-sectional Dutch stock returns. If the leverage factor can explain stock variations, the implication is that stocks that positively correlate with the leverage factor should provide greater returns. The assumption is made on the notion that highly levered firms have an advantage in generating higher returns in exchange for bearing higher risk. This hypothesis will be assessed by using both daily and monthly cross-sectional data in accordance with the Fama & French methodology (1992; 2015).

3.2 Hypothesis II: *The Four-Factor Model outperforms both the Three-Factor Model and the CAPM Model and has a stronger predictive power in explaining stock returns.*

The Four-Factor Model refers to the augmented Three-Factor model with financial leverage as an additional factor. Essentially model comparison will be assessed through the joint statistical F-test which will evaluate all the asset pricing models mentioned in this paper such as CAPM, the Three-Factor Model, and the Four-Factor Model. Forecasting will be used to assess their respective predictive abilities. The objective is to select the model with the lowest predicting error, and the most precise regression line of fit. All the analyses will be performed for both the daily and the monthly data.

4. Data

To examine the relationship between financial leverage and cross-sectional stock returns, AEX index constituent prices are used, in the period of 1999-2020. The AEX index, derived from the Amsterdam Stock Exchange, is a stock market index composed of Dutch companies that trade on Euronext Amsterdam. The index, debuted in 1983, consists of the most traded 25 constituents on the exchange with a market capitalization of €850,8 billion as of March 2021 (Euronext, 2021).

Compustat Global of Wharton Data Services (WRDS) is used to retrieve stock prices of of the AEX index constituents. The Bloomberg database is used to retrieve the respective company financials of the AEX constituents. The company financials data include total assets, total liabilities, total debt, and shares outstanding).

Bloomberg is similarly used for retrieving the price of the AEX index and the German 10-year bond. The AEX index is a capitalization-weighted[5] index acting as the regional market representation of the Dutch companies that is later used for calculating the market return. The German 10-year bond is used as the risk-free rate. German 10-year bonds are considered the safest in the European framework, making them a superior benchmark for the Dutch stock market. They are both obtained for the period of 1999-2020.

The entire research population is essentially the Dutch stock market. Given the importance of financial leverage in stock returns and the debate around it, there is little evidence of its significance in the Netherlands. Thus, the goal is to provide further research of the robustness of the Fama & French Three-Factor Model and the prominence of financial leverage in the Dutch stock returns. The AEX index contains the most representative companies of the Dutch stock market. This is attributable to the fact that AEX lists the most actively traded Dutch equities, which reflects the strength of the Dutch economy.

5. Methodology

In asset pricing, multi-factor models follow the Fama & French approach which expands on the CAPM, by deriving plausible factors that tend to explain the variations in cross-sectional stock returns (Fama & French, 1992, 2015). A multi-factor model is a financial model that uses many factors to explain market events and/or equilibrium asset valuations. It can be used to describe a single security or an entire portfolio of securities. It accomplishes this by comparing two or more variables in order to understand the correlations between variables and the ensuing performance (Chen, 2021).

Hence, this research will calculate the CAPM model, following Sharpe & Lintner methodology (1964; 1965). It will also further adopt the Fama & French methodology to calculate the Three-Factor Model and its augmented version, the Four-Factor Model.

5.1 The Four-Factor Model

The Four-Factor model builds on the CAPM and the Three-Factor model by adding financial leverage as its fourth factor. The goal is to see how important leverage is in

[5] The AEX index is a capitalization-weighted index because each constituent index weighting caps at 15% annually.

explaining Dutch stock returns and if this model beats the Three-Factor Model. The Four-Factor model is derived in equation 3.

$$R_{it} - r_f = \alpha + \beta_i \left(R_m - r_f\right) + s_i SMB + h_i HML + l_i HLMLL + e_{it} \quad (\mathbf{3})$$

Adapted source: (Mirza et al., 2013).

In equation 3, the fourth factor HLMLL (high-leverage-minus-low-leverage) represents financial leverage. Financial leverage is the capital mix that companies employ to fund their asset base, and it shows a company's ability to obtain additional cash to keep its operations running (Mirza et al., 2013). It proxies the impact that high levered firms have compared to that of low levered firms. The derivation of each factor is based on portfolio sorting. Portfolio sorting is a tool that is used in empirical finance to test asset pricing models, detect pricing anomalies, and develop effective investment strategies (Ernstberger et al., 2011). It refers to the idea of grouping stock returns into portfolios based on some firm characteristics. The firm characteristics that portfolios sort the companies by are size, value, and financial leverage. These help us build the right-hand-side (RHS) factors that in turn will explain the left-hand-side (LHS) stock returns of the AEX index.

Size, represented by the SMB factor, is characterized by market capitalization (M), defined in equation 4. It simply reflects whether the company is considered as small or big.

$$M = Shares\ Outstanding\ x\ Price \quad (\mathbf{4})$$

The HML factor, representing the value of a company is calculated through the book value/market value (B/M) ratio, equation 5. B/M depicts whether the company is undervalued or overvalued by comparing its fundamental value to the value that the market perceives it at. Hence it is meant to determine the value factor, equation 5.

$$\frac{B}{M} = \frac{Total\ Assets - Total\ Liabilities}{Market\ Cap} \quad (\mathbf{5})$$

Lastly, the HLMLL factor, indicating financial leverage, is calculated through D/A, equation 6. This ratio depicts the amount of debt a company uses to finance its assets (Andrew Bloomenthal, n.d.).

$$\frac{D}{A} = \frac{Long\ Term\ Liabilities + Current\ Liabilities}{Total\ Debt + Owner's\ Equity} \quad \mathbf{(6)}$$

5.2 Dependent Variable

The outcome variable also known as the dependent variable will be the LHS stock premium. This is the case for CAPM, the Three-Factor and Four-Factor model, respectively equations 1, 2 & 3. The stock premium refers to the difference between the AEX constituent stock return and the German risk-free rate ($R_{it} - r_f$). The stock return is calculated by taking the % change of the AEX constituent stock prices between the current period and the previous period. The AEX constituent stock prices are retrieved from WRDS accordingly to their inclusion period in the AEX index. All additional pricing and financial data are deleted during the period the components were not in the AEX index. The initial entry for each AEX constituent is removed since it would not have a return if the preceding price was when the constituent in question was not in the AEX index.

It is important to note that each stock premium is equally weighted meaning that each AEX constituent stock return is given the same weight or importance, irrespective of their market capitalization (Chen, n.d.).

5.3 Independent Variables

The first independent variable in all the models is the market premium, equations 1, 2 and 3. The market premium refers to the difference between the AEX market return and the German risk-free rate $(\mathrm{R_m} - \mathrm{r_f})$. The market return is the % change of the AEX index prices between the current period and the previous period. The AEX index price is obtained from Bloomberg, and its corresponding return is synced with the AEX constituent return for the same time period.

Moving on to the following independent variables, each factor computation will be discussed. The creation of the SMB and HML factors follow the methodology of (Fama & French, 1992, 2015). The HLMLL factor is adapted from other prominent studies such as that of Sivaprasad & Muradoglu (2011) and Mirza et al. (2013). However, it still follows the concept of portfolio sorting and factor creation of Fama & French (1992; 2015).

5.3.1 Portfolio Sorting

According to the Fama & French (1992; 2015) approach, factor formation is performed through portfolio sorting. Hence, all data is separated into portfolios starting from $July_t - June_{t+1}$. This six-month delay is necessary to avoid the look ahead bias by ensuring that all the accounting data updates are incorporated, Fama & French (1992; 2015). This means that only constituents included in the AEX index within $July_t - June_{t+1}$ are included. For the period of 1999 – 2020, a total of 70 companies were part of the AEX index. Some stock return outliers were removed due to the inconsistencies they had with the other databases data. This measurement error could have led to an outlier bias in the dataset. The Three-Factor Model will calculate the SMB and HML factor based on a 2 x 3 portfolio sorting. Whereas the Four-Factor Model will use a 2 x 3 x 3 portfolio sorting.

5.3.2 Data Frequency

Each model estimation will be tested with two different data frequencies. The first data frequency will be daily consisting of daily stock returns, daily market returns and daily factor formations. Whereas, the second frequency will be monthly consisting of monthly stock returns, monthly market returns and monthly factor formation. Factor formation in both the daily and monthly models will make use of annual portfolio sorting of various companies with regards to size, value, and financial leverage. We want to see whether daily data gives different results due to its random noise compared to monthly data.

5.3.2 Factor Formation

The 2 x 3 portfolio sorting will be formed by splitting the stock returns in two categories. Below the median of the dataset will be considered as the small sized companies (S). Above the median will be considered as the big sized companies (B). This is decided based on the constituents' market capitalization, equation 4.
After this division, each size category is further split into three other value categories. The first value category refers to above the 70^{th} percentile of the dataset, resulting from a high B/M ratio, equation 5, and indicating undervaluation (L). In the next category, there's below

the 30^{th} percentile of the dataset, consisting of a low B/M ratio and indicating overvaluation (H). Everything above the 30^{th} and below the 70^{th} percentile will fall under the third category of neutral (N). For further illustration of 2 x 3 portfolio sorting, refer to Table 5.1.

Table 5.1 2 x 3 Portfolio Sorting Procedure for the Three-Factor Model

Size	**Value**	**Portfolios**
	High B/M	BH
Big M	Neutral B/M	BN
	Low B/M	BL
	High B/M	SH
Small M	Neutral B/M	SN
	Low B/M	SL

Adapted source: (Mirza et al., 2013).

After the 2 x 3 portfolio sorting, the SMB and HML factors can be calculated[6]. SMB is calculated by taking the difference between the equally weighted average of the returns of all small companies' portfolios minus the average returns of all big companies' portfolios (small-minus-big), as in equation 7.

$$SMB = \frac{1}{3}(SH + SN + SL) - \frac{1}{3}(BH + BN + BL) \quad (\mathbf{7})$$

In a similar manner, HML is calculated by taking the difference between the average of all value companies' portfolios minus the average of all growth companies' portfolios (high-minus - low), as in equation 8.

$$HML = \frac{1}{2}(BH + SH) - \frac{1}{2}(BL + SL) \quad (\mathbf{8})$$

Next, 2 x 3 x 3 portfolio sorting is considered for the Four-Factor Model, shown in Table 5.2. Essentially, additional sorting of leverage into three categories is added to the previous Three-Factor Model portfolio sorting, Table 5.1. The three categories include: above 70^{th} percentile

[6] Both SMB and HML factors are self-calculated by using Python, hence they are not retrieved from the Kenneth R. French website - http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

referring to the high levered companies (HL), below the 30^{th} percentile referring to the low levered companies (LL), and everything in between would belong to neutral levered companies.

Table 5.2 2 x 3 x 3 Portfolio Sorting Procedure for the Four-Factor Model

Size	Value	Leverage	Portfolios
	High B/M	High Leverage	BHHL
		Low Leverage	BHLL
Big M	Neutral B/M	High Leverage	BNHL
		Low Leverage	BNLL
	Low B/M	High Leverage	BLHL
		Low Leverage	BLLL
	High B/M	High Leverage	SHHL
		Low Leverage	SHLL
Small M	Neutral B/M	High Leverage	SNHL
		Low Leverage	SNLL
	Low B/M	High Leverage	SLHL
		Low Leverage	SLLL

Adapted source: (Mirza et al., 2013).

As indicated in Table 5.2, financial leverage sorting will only consider the two most relevant categories, those being high leverage firms (highest D/A) and low leverage firms (lowest D/A). These two extremes are thought to show a bigger contrasting effect of how leverage affects the stock price and firm value in general. As a result, the high D/A value is extracted from above the 70^{th} percentile of the dataset and the low D/A value is extracted from below the 30^{th} percentile (Muradoglu & Sivaprasad, 2008). In turn, this will help calculate the HLMLL factor[7] by taking the difference between the equally weighted average returns of all high levered companies' portfolios minus the average returns of all low levered companies' portfolios (high-leverage-minus-low-leverage), equation 9. The high D/A ratio corresponds to the top 21 companies with the highest leverage ratio out of 70 companies in total. The low D/A ratio corresponds to the bottom 21 companies with the lowest leverage ratio. This indicates that 60% of the companies will be used in the portfolio construction of the HLMLL

[7] The HLMLL factor is also self-calculated using Python and not retrieved from any other data library.

factor which is more than the average of the initial number of firms. Moreover, the same number of firms is also used in the portfolio construction of the HML factor due to the same percentile benchmarks.

$$HLMLL = \frac{1}{6}(BHHL + BNHL + BLHL + SHHL + SNHL + SLHL) - \frac{1}{6}(BHLL + BNLL + BLLL + SHLL + SNLL + SLLL) \quad \mathbf{(9)}$$

5.4 Descriptive Statistics

The main features of the data are described in this section. Firstly, descriptive statistics tables will be provided for each equally weighted portfolio sorting: i.e.: 2 x 3[8] and 2 x 3 x 2[9], for both the daily and monthly data, Table 5.3, and Table 5.4, respectively in the period of 1999-2020. Table 5.3 shows the average value and standard deviation of the Dutch stock premium percentages ($R_{it} - r_f$) that belong to the respective 2 x 3 portfolio sorting. Overall, the only negative average stock premiums appear in in Row 3 of small sized companies. This represents negative performance of the AEX small constituents in all the value sorting, Row 2, except the monthly small and value positive performance of 0.067. On the contrary, all the big sized AEX constituents, Row 4, seem to reflect positive performance throughout the period of 1999-2020, both in a daily and monthly manner. Generally, the standard deviations of the monthly portfolio sorting are higher than the daily ones because there seems to be more variability of the stock premiums on the monthly basis rather than on the daily basis. Thereby, this makes the monthly data distributions more widely dispersed.

Table 5.3 Descriptive statistics of the 2 x 3 portfolio sorting

	Daily			Monthly		
	Value	**Neutral**	**Growth**	**Value**	**Neutral**	**Growth**
Small	-0.005	-0.002	-0.004	0.067	-0.134	-0.089
	(0.988)	(1.032)	(1.056)	(5.098)	(5.355)	(5.262)
Big	0.000	0.009	0.023	0.128	0.218	0.485

[8] 2 x 3 portfolio sorting is used only in the Three-Factor Model because portfolios are sorted in terms of size (SMB) and value factors (HML).
[9] 2 x 3 x 2 portfolio sorting is used only in the Four-Factor Model because portfolios are sorted in terms of size (SMB), value (HML), and financial leverage factor (HLMLL).

	(1.059)	(1.001)	(1.002)	(5.246)	(5.246)	(5.052)

Notes: 2 x 3 portfolio sorting refers to Column 1 representing the size sorting in terms of small and big market capitalization, and Row 2 representing the value sorting in terms of value (high B/M), growth (low/ B/M), and neutral with everything in between. Mean is shown as the first value and standard deviation is shown second in parentheses.

In the following descriptive statistics Table 5.4, the average Dutch stock premium percentages and their respective standard deviations are shown for the 2 x 3 x 2 portfolio sorting. With the inclusion of financial leverage as part of the portfolio sorting, what stands out is that the average values of all small and low-levered (LL) companies, Row 4, is negative both for daily and monthly models. This indicates that small-cap AEX constituents that are also low-levered, performed negatively in the period of 1999-2020. The only other negative value is the daily average stock performance of AEX constituents that are big-cap and highly levered (HL), Row 6. Note that, all the other big-cap stocks show a positive performance. Henceforth, it appears to be that in general firms that are highly levered perform better than the low levered firms and this distinction is mostly made in small-cap stocks.

Table 5.4 Descriptive statistics of the 2 x 3 x 2 portfolio sorting

	Daily						Monthly					
	Value		Neutral		Growth		Value		Neutral		Growth	
	HL	LL	HL	LL	HL	LL	HL	LL	HL	LL	HL	LL
Small	0.012	-0.017	0.007	-0.009	0.012	-0.017	0.096	-0.288	0.229	-0.088	0.288	-0.096
	(1.052)	(1.001)	(1.021)	(1.040)	(1.052)	(1.001)	(5.285)	(5.315)	(5.394)	(4.905)	(5.284)	(5.315)
Big	0.018	0.027	0.012	0.007	-0.029	0.024	0.418	0.324	0.159	0.266	0.347	0.234
	(1.045)	(0.965)	(1.010)	(1.000)	(1.051)	(1.064)	(5.264)	(5.212)	(4.879)	(5.044)	(4.786)	(4.941)

Notes: 2 x 3 x 2 portfolio sorting refers to Column 1 representing the size sorting in terms of small and big market capitalization, Row 2 representing the value sorting in terms of value (high B/M), growth (low B/M), and neutral with everything in between, and Row 3 representing the financial leverage sorting in terms of high leverage (HL) and low leverage (LL). Mean is shown as the first value and standard deviation is shown in parentheses.

The next following descriptive statistics will be presented about the daily and monthly Four-Factor Model, Table 5.5, and the CAPM and the Three-Factor Model descriptive statistics will be exhibited in Appendix A, Table A1 and Table A2, respectively.

Columns 2 & 7 of Table 5.5 are what determine whether the data is daily or monthly. As shown in the table, each daily variable consists of 70,484 observations. On the contrary, there are only 3,529 observations for the monthly variables, which is around 20 times less than the daily ones. The high daily number of observations contributes to a lot of variability and random noise in the 4 . That could potentially decrease the robustness and the accuracy of the results. Hence this will be further discussed once the results are analyzed.

Columns 3 & 8 represent the average percentage returns of its respective variable. In the daily data, the only independent variable that has a positive mean value is the market premium. This confirms the CAPM expectations. CAPM, as discussed in the literature review, suggests that systematic risk positively affects expected stock returns. This is also seen both in the CAPM Model, Table A1, and the Three-Factor Model, Table A2, Appendix A. Next, the SMB factor has a negative mean return both in the daily and monthly models opposing the expectation that smaller firms explain higher returns than bigger firms. This result contradicts the size effect. Likewise, HML also shows a negative mean return both in daily and monthly data which is inconsistent with the value effect that value stocks, high B/M, explain higher returns than growth stocks, low B/M (Rosenberg et al., 1985). Similar results can be seen in the Three-Factor Model as well, Table A2, Appendix A.

Proceeding with our HLMLL factor of interest, a negative mean return of -0.679 is depicted in the daily data similarly contradicting the expectation that highly levered firms explain higher returns rather than low levered firms. Initially, this expectation was proposed by Modigliani & Miller (1958), who proposed that financial leverage increases the firm's equity return indicating higher stock prices. Additionally, according to the corporate finance theory, higher financial leverage allows for interest tax shield that can contribute to higher profits if the firm is operating above its break-even point. In respect to that, the monthly HLMLL factor does confirm the financial leverage expectation. Its mean value of 24.572 is positive and much larger than the daily mean value. This is in line with the expectation that higher financial leverage indicates higher stock returns compares to low levered firms. Moreover, both the daily and monthly HLMLL mean value also have a corresponding severely high standard deviation of 53.640 and 55.489 respectively. This suggests that the financial leverage data is widely spread. The analysis regarding whether daily or monthly data provides a better model fit will be discussed in the regression results section.

Table 5.5 Descriptive statistics of the daily and monthly Four-Factor Model

	Daily					Monthly				
Variable	**Obs.**	**Mean**	**Std. dev.**	**Min**	**Max**	**Obs.**	**Mean**	**Std. dev.**	**Min**	**Max**
Stock Prem.	70,484	0.005	1.021	-2.285	2.266	3,529	0.142	5.139	-11.304	11.102
Market Prem.	70,484	0.028	0.802	-2.109	2.223	3,529	0.327	3.721	-9.537	8.018
SMB	70,484	-0.025	4.752	-21.512	197.337	3,529	-0.263	2.369	-5.184	6.763
HML	70,484	-0.368	6.739	-16.739	16.839	3,529	-0.219	6.886	-22.825	18.891
HLMLL	70,484	-6.079	53.640	-115.490	68.836	3,529	24.572	55.489	-70.525	90.347

Notes: "Obs." refers to number of observations of the specific variable in the respective dataset."Std. dev." refers to the standard deviation (the extent deviation from the mean) of the specific variable in the respective dataset. "Stock Prem." refers to the stock premium ($R_{it} - r_f$). "Market Prem." refers to the market premium ($R_m - r_f$)."Market Prem." refers to the market premium ($R_m - r_f$).

The last data feature that will be discussed is the unique correlation coefficient between each variable of the Four-Factor Model, Table 5.6. This correlation coefficient value is also known as the Pearson's Correlation, which indicates the strength and the direction of the relationship between two variables of a linear regression model. As shown in Table 5.6, the variable market premium has the strongest positive relation with the variable stock premium, both in the daily and monthly data. This further confirms the expectations and significance of CAPM validating the presence of the relationship between market systematic risk and expected returns (Lintner, 1965; Sharpe, 1964). The same significant outcome is also shown in the CAPM Model, Table A3, and the Three-Factor Model, A4, Appendix A. This is contrary to the results of Fama & French (1992) which show that there is no reliable relation between stock returns and market beta but that there is a strong relation between stock returns and size. In respect to that, we found a negative mean value of the SMB factor, Table 5.6, which is also indicated by a significantly weak and negative relationship of -0.056 and -0.051 with the stock premium, in daily and monthly data respectively. The SMB factor also has a negative correlation coefficient with the market premium which refutes the size effect because smaller stocks are expected to have higher market betas than bigger stocks, according to Fama & French (2015). This negative correlation is seen both in the data and monthly data, -0.210 and -0.238, respectively. The HML factor correlations are surprising. The correlation between HML and stock premium is insignificant and negative both in the daily and monthly data. This is similarly different from the Fama & French (1992) finding that stock returns have a strong positive relation with the value effect. The correlation of HML with market premium is significantly positive both in the daily and monthly data. However, the HML correlation with SMB is significantly positive in the daily data and insignificant in the monthly data. An insignificant monthly correlation between SMB and HML suggests that there is no multicollinearity between the two factors, hence it affirms their purpose of representing different risk factors (Fama & French, 2015).

Lastly, the HLMLL factor seems to have a significant relation with each variable, except the monthly SMB and HML factor. The significant monthly correlation of -0.021 with the stock premium indicates a weak negative correlation with the expected stock returns. Nevertheless, most importantly, the low and insignificant monthly HLMLL correlations with the SMB and the HML factors demonstrates that the SMB and HML factors do not necessarily subsume the similar effects that financial leverage can have on stock returns.

Table 5.6 Correlation table for the daily and monthly variables of the Four-Factor Model

	Daily					Monthly				
Variable	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
1 Stock Prem.	1.000					1.000				
2 Market Prem.	0.427*	1.000				0.465*	1.000			
	(0.000)					(0.000)				
3 SMB	-0.056*	-0.210 *	1.000			-0.051*	-0.238*	1.000		
	(0.000)	(0.000)				(0.003)	(0.000)			
4 HML	-0.003	0.028*	0.059*	1.000		-0.000	0.047*	0.023	1.000	
	(0.435)	(0.000)	(0.000)			(0.994)	(0.005)	(0.178)		
5 HLMLL	-0.025*	-0.021*	0.018*	0.001*	1.000	-0.021*	-0.048*	-0.025	-0.001	1.000
	(0.000)	(0.000)	(0.000)	(0.126)		(0.210)	(0.005)	(0.136)	(0.996)	

Notes: The asterisk indicates that the variable is statistically significantly correlated with its other respective variable at 5% significance level. P-value is shown in parentheses. The correlation coefficient is significant if P-value < 0.05.

5.5 Model Performance and Out-Of-Sample Forecasting

In the Fama & French methodology and in traditional asset pricing, Ordinary Least Squares (OLS) regression is usually used to explore the behavior of various risk factors on expected returns (Zdaniuk, 2014). Risk factors are expected to have a linear relationship with the estimated stock returns. The same assumption and expectation are followed in this paper as well. This type of least squares method minimizes the sum of the squared errors. Error refers to the difference between the observed depended variable i.e., the stock premium, and the predicted variables by the independent variables i.e., the market premium and the factors.

In the end, the question is whether the Four-Factor Model outperforms the Three-Factor Model and the CAPM in explaining stock returns. Thereby, model comparison against each model is performed by using GRS testing, as per Fama & French (2015). The GRS test was formulated by Gibbons et al., (1989) and it runs on the following hypotheses:

$$H_0: joint\ \alpha\ is\ not\ significantly\ different\ from\ zero$$
$$H_a: joint\ \alpha\ is\ significantly\ differeent\ from\ zero$$

If intercept α is significantly different from zero, it essentially means that some pricing error exists. This indicates that the factors do not fully capture the variations of the stock returns. If intercept α is not significantly different from zero, then the factors fully capture the variations in stock returns and there is not pricing error. Therefore, each model will be tested whether its intercept significantly differs from zero. The GRS test statistic is calculated as follows:

$$GRS = \left(\frac{T}{N}\frac{T-N-L}{T-L-1}\right)\left[\frac{\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}}{1+\bar{\mu}'\hat{\Omega}^{-1}c}\right] \sim F\ (N, T-N-L)\ (\mathbf{10})$$

In equation 9, $\hat{\alpha}$ is an N x 1 vector of intercepts, $\hat{\Sigma}$ is an unbiased estimate of the residual covariance matrix, $\hat{\alpha}$ is an L x 1 vector of the sample means of the factor portfolios and $\hat{\Omega}$ is an unbiased estimate of the covariance matrix of the factor portfolios (*GRS Review. Karl Diether University of Chicago Graduate School of Business. Nov 14, L β i j (F Jt) + ε It, i = 1...N, - PDF Free Download*, n.d.).

Furthermore, out-of-sample forecasting is used to compare the predictive abilities of each model. OLS regressions are performed for all the models, equations 1,2 & 3, only in the period of 1999-2014. Then their respective coefficients are used to build separate Mean Squared Errors (MSE) for each model, equation 11.

$$MSE = \frac{1}{N}\sum_{i=0}^{N}(y_i - \bar{y}_i)^2 \quad (\mathbf{11})$$

MSE is a loss function that measures the average squared difference between the predicted values and the actual values. The actual values (y_i) refer to the true values of each stock premium in the out-of-sample period of 2015-2020. The predicted values of each stock ($\bar{y}_i$) are calculated as outputs from the regression coefficients of the period 1999-2014 and the independent variables of the period 2015-2020. The sum of the squared difference between the actual value and the predicted value of each stock premium *(i)*, is then divided by the total number of true stock premiums in the period of 2015-2020. The total amount of observations reaches 18338 for each model. MSE will be used as a model evaluation method that will aid to pick the model with the least forecasting errors.

The year 2014 is picked as the cutoff year because in that year, the Dutch Central Bank (DNB) imposed a higher minimum Tier 1 leverage ratio[10] regulation for banks from 3% to 4% (*Basel III Leverage Ratio Framework and Disclosure Requirements*, 2014). The greater the Tier 1 leverage ratio, the more likely the bank can withstand a negative shock to its balance sheet (Murphy, n.d.). The regulation restrictions could increase operational and funding costs in the financial sector, but they also had the potential to improve the reputation of the banks by increasing their solvability. Despite the increase of financial stability, higher costs can also decrease profitability for banks hence negatively affecting their stock market returns.

We expect that the effect of this structural break would only show in the presence of the financial leverage factor, meaning in the Four-Factor Model rather than in Three-Factor Model or the CAPM Model. The rationale for this is that changing a bank's leverage ratio might potentially raise operational and funding costs in the financial sector while also while also boosting the bank's reputation in the financial market. The leverage risk factor would reveal this reform more than the firm's size or value risk factor. It also is important to note that the Tier 1 leverage structural change only applies to banks' leverage ratios, not other businesses' leverage ratios. As a result, a 1% change in the Tier 1 leverage ratio may only have a minor impact on the MSE reliability of the Four-Factor Model.

The objective is to be aware of the existence of this structural break in case the Four-Factor Model has huge forecasting errors relative to the models that do not include the leverage factor.

[10] Tier 1 leverage ratio measures the bank's core capital relative to its assets.

6. Results & Discussion

First and foremost, Hypothesis I will be assessed. Hypothesis I states that financial leverage factor (HLMLL) is a significant factor that positively affects stock returns, implying that highly levered firms yield higher returns compared to low levered firms. In Table 6.1, the HLMLL factor seems to be a significant factor, P-value < 0.005, only in the daily Four-Factor Model and not in the monthly dataset. However, its daily value of -0.000 indicates almost no relationship because it means that for one unit change of the daily HLMLL, there will be an almost zero unit change of the daily stock premium, the unit in these calculations being the percentage returns. Hence, the daily HLMLL denies the implication of Hypothesis I because it does not show that daily financial leverage is a positive factor in explaining Dutch stock returns. In a similar manner, the HML factor seems to be a significant factor only in the daily model and an insignificant factor in the monthly model. Its negative daily coefficient of -0.003 opposes the expectation of Fama & French (1992; 1995) that value companies explain higher stock returns than growth companies. The only two factors that are significant both in the daily and monthly framework, are the market premium and the SMB factor. Likewise, they both indicate a positive relationship with the average stock returns. This is in line with the expectation and results of Fama & French (1992; 2015) expectations. Similar conclusions about the SMB, HML and market premium variables can also be reached from Table B1 and Table B2, Appendix B. The exceptionally low coefficients of SMB and HML are attributable to the fact that AEX constituents generally reflect firms with a larger market capitalization than the AMX (mid-cap) and AScX (small-cap) indices (*Analysing the Price of the Dutch AEX Index before Trading*, n.d.) As a result, it's likely that the AEX constituents' market capitalization range doesn't contain small enough firms for the size effect to be noticeably represented in the SMB factor. The same holds for the value effect, since the AEX index constituents may not have a low enough B/M ratio for the HML factor to show up considerably.

In conclusion, the HLMLL factor fails to reject the null hypothesis of Hypothesis I. The reason being is that even though the daily HLMLL factor is a significant factor, it still does not indicate a positive relationship as Hypothesis I suggests. Moreover, in the monthly framework, the HLMLL financial leverage factor is not significant.

Table 6.1 Linear regression results for the daily & monthly Four-Factor Model

	Daily		Monthly	
Indep. Variable	**Coefficient**	**P-value**	**Coefficient**	**P-value**
Market Prem.	0.555	0.000**	0.665	0.000**
	(0.004)		(0.021)	
SMB	0.008	0.000**	0.140	0.000**
	(0.001)		(0.033)	
HML	-0.003	0.000**	-0.018	0.104
	(0.001)		(0.011)	
HLMLL	-0.000	0.000**	0.000	0.815
	(0.000)		(0.001)	
Constant	-0.013	0.000**	-0.051	0.547
	(0.00)		(0.084)	
Observations	70,484		3,529	
R^2	0.185		0.221	
Adj. R^2	0.184		0.220	

Notes: The standard errors are shown in parentheses. Market Prem refers to Market Premium. Adj. R^2 refers to adjusted R^2. The asterisks refer to 5% significance level, ** P-value < 0.05.

The second hypothesis will be assessed next. Hypothesis II states that the Four-Factor Model outperforms the Three-Factor Model and the CAPM Model. Outperformance will be evaluated through GRS testing. As explained in section 5.4, the GRS test tests whether the regression intercepts α_i of all the models are jointly zero. The GRS null hypothesis H_0 is rejected if an α_i intercept is significantly different from zero, implying that pricing error is not fully eliminated, hence the model does not fully explain the expected stock returns. However, what's key here is that GRS testing allows for relative model comparison, meaning that even if the models do not fully explain the expected returns, it can show you which model is doing better than the other (Fama & French, 2015).

Table 6.2 and Table 6.3 provide GRS testing results for the daily and monthly data of CAPM, Three-Factor Model and Four-Factor respectively. Table 6.2 clearly shows that the GRS test statistic increases consecutively with each daily model, from the CAPM to the Four-Factor Model. When it comes to the efficacy of the model, a larger GRS statistic is undesirable. It is undesirable because it implies that the value of the α's is jointly different from zero. This indicates a higher pricing error. This is observed with the addition of a new factor as the GRS statistic increases from 8.546 to 10.374 and to 14.101 for each model respectively, Table 6.2. The same conclusion is reached considering that the lowest mean $|\alpha|$ represents the best model with the least pricing error, by extension suggesting that the factors effectively explain the variations of the stock returns. In that case, CAPM again has the lowest mean $|\alpha|$ of 0,010 correspondingly with the lowest GRS test statistic of 8.546.

The P-value is strongly significant for all the models, P-value < 0.005, suggesting that the models' α intercept is significantly different from zero, hence GRS H_0 is rejected. The lower the P-value, the more likely it is to reject the H_0, which means the further away α is from zero. Following that logic, all the three daily models seem to not fully explain the expected returns since they all consist of a significant unexplained part which is also considered as pricing error. In addition, the mean adjusted $\left|R^2\right|$ seems to be the lowest for CAPM, 0.183 and the same value for both the Three-Factor Model and the Four-Factor Model, 0.184. The slight increase for the latter models might potentially be due to overfitting, making it trivial. Nonetheless, the low GRS statistic and the mean $|\alpha|$ lead to the conclusion that the daily CAPM Model outperforms the other two factor models. Lastly, the GRS statistic of the Three-Factor Model suggests a better performance relative to the Four-Factor Model. To sum up, the relative performance of the daily Four-Factor does not reject the null hypothesis of Hypothesis II.

Table 6.2 GRS testing results for the daily CAPM, Three-Factor & Four-Factor Model

	CAPM	**Three-Factor Model**	**Four-Factor Model**
GRS test statistic	8.546	10.374	14.101
P-value	0.003**	0.001**	0.002**
Mean $\lvert\alpha\rvert$	0.010	0.011	0.013
	(0.003)	(0.003)	(0.004)
Mean adj. $\lvert R^2\rvert$	0.183	0.184	0.184

Notes: Daily data considers 70,484 observations. Mean adj. $|R^2|$ refers to mean adjusted absolute $|R^2|$. The values in parentheses refer to the standard errors of the mean absolute $|\alpha|$. The asterisks refer to 5% significance level. ** P-value < 0.05.

In the monthly framework, Table 6.3, the P-values of all the three models are strongly insignificant, not rejecting the H_0, implying that there is no unexplained part left in the model meaning that all the independent variables fully explain the expected stock returns. The Three-Factor Model shows the highest P-value, the CAPM model shows the lowest P-value, and the Four-Factor Model falls in the middle. The similar order of relative model performance can be observed through the GRS statistics and the mean $|\alpha|$. The monthly Three-Factor has the lowest GRS statistic of 0.309 and the lowest mean $|\alpha|$ of 0.043, indicating that monthly SMB and HML factors explain the expected stock returns in the most effective way with the least pricing error. Similarly like in the daily data, the mean adjusted $|R^2|$ is the lowest for CAPM and stays the same for the other two models. To conclude, the monthly results of Table 6.3 also do not reject the null hypothesis of Hypothesis II because even though the monthly Four-Factor outperforms the CAPM, it doesn't outperform the Three-Factor Model.

Table 6.3 GRS testing results for the monthly CAPM, Three-Factor & Four-Factor Model

	CAPM	**Three-Factor Model**	**Four-Factor Model**
GRS test statistic	0.788	0.309	0.363
P-value	0.375	0.579	0.547
Mean $|\alpha|$	0.068	0.043	0.051
	(0.077)	(0.077)	(0.084)
Mean adj. $|R^2|$	0.216	0.220	0.220

Notes: Monthly data considers 3,529 observations. Mean adj. $|R^2|$ refers to mean adjusted absolute $|R^2|$. The values in parentheses refer to the standard errors of the mean absolute $|\alpha|$. The asterisks refer to 5% significance level. ** P-value < 0.05.

Given that the GRS test yields different findings about the relative performance of the daily and monthly models, it is interesting to compare the prediction ability of the models over the two data frequencies. This is a measure that recommends choosing a model based on its forecasting performance. As previously mentioned, forecasting performance may be evaluated using MSE calculations. A lower MSE indicates a model with a lower forecasting error, suggesting that the difference between the predicted values and the actual values is smaller. That means that the fitted model predicts the out-of-sample forecasts more accurately, implying that you are getting closer to finding the line of best fit. In Table 6.4, the Three-Factor Model in Column 1, shows the lowest MSE of 0.752, suggesting that it is the best daily fitted model to predict the out-of-sample forecast from 2015-2020. The Four-Factor Model seems to be the second best daily fitted model with an MSE of 0.753. Whereas CAPM is the last one with an MSE of 0.754.

In the monthly data of Table 6.6, Column 2, the best predicting model seems to be again the Three-Factor Model with the lowest MSE of 20.143. In the daily data, the Four-Factor Model is the second best monthly fitted model with a slightly higher MSE of 20.148. Lastly, CAPM turns out to predict forecasts less accurately with the highest MSE disparity of 20.273. Overall, the MSE among the daily data models and monthly data models differ slightly. Particularly, the Four-Factor Model MSE increases from that of the Three-Factor Model by 0.001 and 0.005, in the daily and monthly data respectively. This demonstrates that the Tier 1 leverage ratio reform had no adverse influence on the MSE of the Four-Factor Model, suggesting that the structural break had no significant impact on the overall financial leverage risk.

The results of Table 6.4 conclude that the Three-Factor Model out-of-sample forecast is the most accurate with the least squared error both in the daily and monthly data. This contributes to the rejection of Hypothesis II because it again shows that the Four-Factor Model out-of-sample forecast does not outperform the Three-Factor Model forecast.

Table 6.4

MSE results for the daily & monthly CAPM, Three-Factor Model, & Four-Factor Model

	Daily	**Monthly**
CAPM	0.754	20.273
Three-Factor Model	0.752	20.143
Four-Factor Model	0.753	20.148

Furthermore, when comparing daily versus monthly data, daily stock returns are found to be more indicative of data non-normality than monthly stock returns. In comparison to a normal distribution, daily return distributions appear to be more fat-tailed. This can also be seen in our daily stock returns, which contain more observations in the center section and in the extreme tails compared to monthly stock returns. This is the case because random noise is more prevalent in daily returns rather than in monthly data. The leptokurtic property of daily data might explain why we see daily and monthly model discrepancies in each data analysis.

7. Conclusion & Limitations

This research aimed to provide more evidence regarding the significance of financial leverage in explaining Dutch stock returns. This was explored by creating a Four-Factor Model which included financial leverage as the fourth risk factor. Or findings of the OLS regression of the Four-Factor Model showed that only the daily financial leverage factor HLMLL is significant. Irrespective of the significance, the coefficient value was almost zero indicating almost no relationship. Hence, the null hypothesis of Hypothesis I is not rejected, indicating that financial leverage is not significant in explaining Dutch stock returns.

The second hypothesis that the research intended to answer was whether the Four-Factor Model outperforms the Three-Factor Model and the CAPM Model. Again, the implication of Hypothesis II was that the addition of financial leverage would improve the model by allowing it to capture more of the variations of the Dutch stock returns. The findings of our GRS testing showed that the CAPM Model outperformed both the Three-Factor Model and the Four-Factor Model in the daily data with the lowest pricing error. However, in the monthly data, the Three-Factor Model outperformed the other two models. Hence, the null hypothesis of Hypothesis II cannot be rejected because the monthly Four-Factor Model outperforms only the CAPM Model and not the Three-Factor Model.

In addition, the predictive abilities of all the models are assessed through out-of-sample forecasts with the help of MSE calculations. In those forecasts, the Three-Factor Model seems to predict Dutch stock returns from 2015-2020 most accurately with the lowest predicting errors. The Four-Factor Model did not show a much larger MSE due to the structural break of the Tier 1 leverage reform. Moreover, the daily models tend to show non-normality data distribution with more extreme values, compared to the monthly models.

Our findings overall show that financial leverage is not a significant additional risk factor when it comes to explaining Dutch stock returns. This is further shown by the inability to reject both of our hypotheses, Hypothesis I and II.

A limitation to our research methodology is the AEX index constituents sample data. The AEX index is often considered as representative of the Dutch stock market because it consists of the biggest and most important Dutch companies. This sample set limits our research only to large-cap Dutch companies, which might not be a very diverse range for our factors (SMB, HML, & HLMLL) to show their effects significantly. A suggestion for further research would be to include the AMX index (mid-cap) and AScX index (small-cap) into the data sample so that there is a wider range of various sized companies. The AEX sample's survivorship bias is another drawback of our approach. This refers to the fact that we only looked at the constituents who managed to stay in the AEX index rather than those who dropped out.

A limitation concerning the inclusion of financial leverage (D/A) as a risk factor is the choice of measure for leverage. Perhaps, if leverage risk captures equity returns, then other leverage ratios might be able to explain cross-sectional returns better. Similarly, leverage could also be explored across industries separately. That could give more representative HLMLL factors since different industries have different leverage benchmarks.

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Appendix A: Descriptive Statistics

Table A1 Descriptive statistics of the daily and monthly CAPM Model

	Daily					Monthly				
Variable	**Obs.**	**Mean**	**Std. dev.**	**Min**	**Max**	**Obs.**	**Mean**	**Std. dev.**	**Min**	**Max**
Stock Prem.	70,484	0.005	1.021	-2.285	2.266	3,529	0.142	5.139	-11.304	11.102
Market Prem.	70,484	0.028	0.802	-2.109	2.232	3,529	0.327	3.721	-9.537	8.018

Table A2 Descriptive statistics of the daily and monthly Three-Factor Model

	Daily					Monthly				
Variable	**Obs.**	**Mean**	**Std. dev.**	**Min**	**Max**	**Obs.**	**Mean**	**Std. dev.**	**Min**	**Max**
Stock Prem.	70,484	0.005	1.021	-2.285	2.266	3,529	0.142	5.139	-11.304	11.102
Market Prem.	70,484	0.028	0.802	-2.109	2.232	3,529	0.327	3.721	-9.537	8.018
SMB	70,484	-0.025	4.751	-21.512	197.338	3,529	-0.263	2.269	-5.184	6.763
HML	70,484	-0.368	6.739	-16.739	16.839	3,529	-0.219	6.886	-22.825	18.891

Table A3 Correlation table for the daily and monthly variables of the CAPM Model

	Daily		Monthly	
Variable	**1**	**2**	**1**	**2**
1 Stock Prem.	1.000		1.000	
2 Market Prem.	0.427*	1.000	0.465*	1.000
	(0.000)		(0.000)	

Notes: The asterisk indicates that the variable is statistically significantly correlated with its other respective variable at 5% significance level. P-value is shown in parentheses. The correlation coefficient is significant if P-value < 0.05.

Table A4 Correlation table for the daily and monthly variables of the Three-Factor Model

	Daily				Monthly			
Variable	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
1 Stock Prem.	1.000				1.000			
2 Market Prem.	0.427*	1.000			0.465*	1.000		
	(0.000)				(0.000)			
3 SMB	-0.056*	-0.210*	1.000		-0.051*	-0.238*	1.000	

	(0.000)	(0.000)			(0.003)	(0.000)		
4 HML	0.003	0.028*	0.059*	1.000	-0.000	0.0047*	0.023	1.000
	(0.435)	(0.000)	(0.000)		(0.994)	(0.005)	(0.178)	

Notes: The asterisk indicates that the variable is statistically significantly correlated with its other respective variable at 5% significance level. P-value is shown in parentheses. The correlation coefficient is significant if P-value < 0.05.

Appendix B: Regression Results

Table B1 Linear regression for the daily and monthly CAPM Model

	Daily		Monthly	
Variable	**Coefficient**	**P-value**	**Coefficient**	**P-value**
Market Prem.	0.545	0.000**	0.642	0.000**
	(0.004)		(0.021)	
Constant	-0.010	0.003**	-0.068	0.375
	(0.003)		(0.077)	
Observations	70,484		3,529	
R^2	0.183		0.216	
Adj. R^2	0.183		0.216	

Notes: The standard errors are shown in parentheses. Market Prem refers to Market Premium. The asterisks refer to 5% significance level. ** P-value < 0.05.

Table B2 Linear regression for the daily and monthly Three-Factor Model

	Daily		Monthly	
Variable	**Coefficient**	**P-value**	**Coefficient**	**P-value**
Market Prem.	0.555	0.000**	0.665	0.000**
	(0.004)		(0.021)	
SMB	0.008	0.000**	0.140	0.000**
	(0.001)		(0.033)	
HML	-0.003	0.000**	-0.018	0.104
	(0.001)		(0.011)	
Constant	-0.011	0.001**	-0.043	0.578
	(0.003)		(0.077)	
Observations	70,484		3,529	

R^2	0.184	0.221
Adj. R^2	0.184	0.220

Notes: The standard errors are shown in parentheses. Market Prem refers to Market Premium. The asterisks refer to 5% significance level. ** P-value < 0.05.