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Short-Term Stocks, Long-Term Gains

Leveraging Implied Equity Duration in Portfolio Management

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Abstract

This thesis extends the literature on equity duration by analyzing stock market dynamics, particularly the short duration premium. Utilizing a robust dataset spanning from 1970 to 2022, our approach extends Weber's (2018) work through various analytical frameworks, examining this phenomenon in depth. Significant findings include the identification of a short duration premium in the stock market, where stocks with shorter equity duration consistently outperform those with longer durations. This pattern, stable across various market conditions, challenges traditional asset pricing models, indicating a unique value in shorter-duration stocks. This thesis employed various factor models, from the CAPM to the Stambaugh-Yuan model. Each revealed insights but also significant unexplained returns in our SML-portfolio. This highlights the potential influence of market inefficiencies and behavioral aspects in asset pricing, suggesting new directions for future research in this area.

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1. Introduction

In recent times, the concept of equity duration has gained significant attention in the field of financial economics, prompting extensive research and analysis. A common key finding of the research has been the phenomenon of the short duration premium, which suggest there is a premium for favoring short duration stocks over long duration stocks. Despite numerous studies, such as the notable work by Weber in 2018, there has been little success to fully explain the abnormal returns of the short duration premium. Our thesis aims to revisit Weber's 2018 study, utilizing an updated dataset that spans from 1970 to 2022, and incorporating established and newer factor models. In this thesis, our goal is to contribute to the existing literature of equity duration by exploring the intricacies of the short duration premium and its abnormal returns through the lens of newer financial data and asset pricing models.

The thesis will initially lay a solid foundation by exploring the concept of equity duration through a review of existing literature and frameworks. Subsequently, the thesis details the comprehensive process of data collection, cleansing and the logic behind variable selection, aiming for a transparent and reproduceable analysis. We then move to a comprehensive presentation of the methodological approach for estimating future financial performances, which forms the basis for calculating equity duration. We further describe the process of formulating hypotheses for empirical testing. The focus is on whether the SML-portfolio strategy, which involves holding a long position in short duration stocks and a short position in long duration stocks, generates positive abnormal returns.

Subsequently, the thesis reveals the main findings, beginning with descriptive statistics that lay the basis for a detailed factor model analysis. This section will also explore the efficacy of applying newer asset pricing models such as the q-factor and Stambaugh-Yuan models to recent data. We then compare our results and reflect on the implication of the unaccounted abnormal returns and identify potential directions for future research. The final remarks aim to place the research within the wider context of financial economics, highlighting the importance of further exploration of equity duration.

Within the scope of our thesis, we find evidence of the short duration premium, characterized by the higher returns generated by shorter duration stocks over their long-duration counterparts. This finding is consistent with existing literature as it reveals a downward sloping term structure. This diverges from the upward-sloping or flat structures commonly predicted by traditional asset pricing models. Further we find that none of the asset pricing models, both traditional and newer, can fully account for the abnormal returns observed in the SML-portfolio. This combined with the finding that high duration stocks tend to have higher mispricing scores, may suggest that there are behavioral biases and market inefficiencies that could contribute to the short duration premium.

2. Litterature review[1]

The academic consensus suggests that the term structure of equity yields generally exhibits a downward slope, although some research, such as Schroeder & Esterer (2016), identifies contrasting findings. The downward sloping of the term structure translates to the short duration premium, implying that stocks with a shorter duration, which yields their cash flow sooner, tend to have higher returns. Conversely, stocks with a longer duration, expected to generate a larger portion of their cash flow in the distant future, usually earn lower returns, contributing to the short duration premium.

This finding that the term structure of equity is downward sloping is intriguing, especially when leading asset-pricing models, such as external habit formation model of Campbell & Cochrane (1999) and the long-run risk model of Bansal & Yaron (2004) suggest that the term structure should either be upward-sloping or flat. Numerous studies investigate this phenomenon. They aim to comprehend the reasons behind it by examining the relationship between equity duration and various risk factors that account for the returns associated with different durations. Moreover, some research argue that equity duration may be acting as a proxy for other risk factors that is not considered that generate an alpha. Other research indicates that there are behavioral biases that may contribute to systematic mispricing of short-duration and of high-duration equities.

Goncalves (2021) and Gormsen & Lazarus (2019) present empirical evidence showing that value stocks tend to exhibit attributes like high profitability, high value, low investment requirements, and lower risk relative to growth stocks. As value stocks is often a characteristic of low duration stocks, these are factors that could serve as the underlying factors equity duration are a proxy for. Campbell & Voulteenho (2004) propose that value stocks are subject to a different set of risks compared to growth stocks. This can be seen in the cash-flow model for equity duration, that value stocks (low duration) are more sensitive to immediate cash-flow risks. In contrast, growth stocks (high duration) are more vulnerable to risks that affect the discount rate, which determines the present value of future cash flows. Santos and Vernosi

[1] Influenced by the papers of van Binsbergen & Koijen (2017) and Mullins (2020)

(2005) and Goncalves (2021) back up these findings with empirical support, highlighting how the duration of an equity can signal different types of risks.

Furthermore, Lettau & Wachter (2007), van Binsbergen et al. (2013), van Binsbergen & Koijen (2017), along with Croce, Lettau & Ludvigsson (2015) delve into the behavioral elements that may explain the term structure of equities. This angle provides a potential rationale for the discrepancies observed between the anticipated equity term structure as per traditional asset-pricing models and the actual outcome, which could be influenced by investor sentiment and behavioral biases.

A range of studies have shown that equity duration is not only static but also time-varying. For instance, Goncalves (2021) shows that the volatility inherent in stock returns has a direct impact on equity duration. Similarly, in the research conducted by Broughton & Lobo (2004), they present evidence that growth stocks, which tend to be more volatile, present considerable challenges in forecasting their long-term growth and profitability. This uncertainty plays a significant role in the calculation of equity duration and may also lead to mispricing of the stocks that can further impact the short duration premium.

In the study conducted by Weber (2018), he found that investor sentiment is a key factor that can contribute to affecting the equity duration over time. Baker & Wurgler (2006) present in their study that investor sentiment can lead to fluctuations in valuation of stocks. Their observations indicate that during phases of high-investor sentiment, growth stocks tend to be more overvalued, while value stocks tend to be more undervalued by optimists and speculators in the market due to the prospect of future growth. Conversely, in periods of low investor sentiment, the inverse happens. This pattern is consistent with Weber (2018) that show the short duration premium fluctuates in different phases of investor sentiment.

Studies, such as Dechow, Erhard, Sloan & Soliman (2021), show that the term structure of equities can be inverted during macroeconomic crises. They illustrate how the COVID-19 pandemic, that primarily affected the immediate cash-flows, thereby impacting low-duration stocks. This led to a situation where the short duration premium could turn negative, as investors would adjust their portfolios to accommodate the heightened risk associated with immediate cash-flows. The studies we have covered so far, collectively highlight the time-varying nature of equity duration, such as the volatility of stock returns, changing investor sentiment, and economic disruptions.

3. Discussion

3.1 Equity duration

Equity duration is a nuanced concept in finance, tracing its roots to the idea of bond duration, which measures how much a bond's price is affected by changes in interest rates. Similarly, equity duration attempts to determine how sensitive a stock's price is to shifts in discount rates. At its core, equity duration estimates the duration it takes for an investor to recoup the cost of a stock through the cash flows the stock generates. It serves as a measure of the timing and present value of cash flows an investor anticipates receiving from holding a share of stock. (Dechow, Sloan, & Soliman, 2004)

The calculation of equity duration generally involves estimating the present value of future cash flows a stock is projected to generate over time. This approach bear resemblance to bond duration calculation where each cash flow is weighted by the time until the investor receives it. A common method to compute equity duration employs variations of the Dividend Discount Model (DDM), which estimates a stock's value by summing up the present value of expected future cash flows. (Williams, 1938)

Additionally, similar to bonds, we can divide equity duration into two categories: Macaulay Duration and Modified duration. Macaulay Duration is the weighted average time until a stock's cash flows are received, while Modified duration measures the price sensitivity of a stock to changes in the discount rate (Macaulay, 1938). Grasping these two distinct aspects is essential for a comprehensive understanding and practical use of the concept of equity duration.

An extension of this concept is Implied Equity Duration, which estimates equity duration using market prices and other observable data, thereby providing a market-based measure of equity duration. This is particularly beneficial for deriving real-time or market-driven insights into equity duration (Dechow, Sloan, & Soliman, 2004). The idea of equity duration is also useful when creating investment strategies. It helps investors and portfolio managers align their investments with their financial obligations, handle the risk associated with interest rate changes, and make more informed investment decisions. Moreover, equity duration is valuable for both cross-sectional analysis, which allows for comparison between companies, and time-series analysis, which examines a company's equity duration over time. This versatility makes equity duration a powerful tool in the field of financial research. (Schroder & Esterer, 2016) (Lettau & Wachter, 2007)

3.2 Term structure

The term structure, often referred to as the yield curve, is a foundational concept in finance. It depicts the relationship between interest rates (or yields) and the maturity of debt securities. The term structure provides a visual illustration of how interest rates on bonds vary with their time to maturity. Typically, it is represented by the yield curve, which plots the interest rates of bonds of equal credit quality against their maturities. (Mishkin & Eakins, 2017)

The shape of the term structure can take three primary forms: upward-sloping (normal), sloping (inverted), or flat. These shapes reflect market expectations about future interest rates and economic activity. For instance, an upward-sloping yield curve suggests that investors expect higher interest rates in the future, which might be due to anticipated economic expansion. Several theories have been proposed to explain the dynamics of the term structure. The Expectations theory states that long-term interest rates are determined by market expectations of future short-term rates. On the other hand, the Liquidity Preference Theory suggest that investors demand a premium for holding long-term bonds due to their greater risk compared to short-term bonds. The Market Segmentation Theory argues that different maturities are traded in segmented markets with their own supply and demand dynamics. (Mishkin & Eakins, 2017)

When applying the term structure to equities, we look at the relationship between the yields and the duration of equites. Understanding the term structure is crucial for many financial activities. These include pricing fixed-income securities, managing interest rate risk, and devising investment strategies. Empirical studies often examine the predictive power of the term structure concerning economic activity and financial market performance (Campbell & Shiller, 1991).

3.3 Asset pricing and factor models

3.3.1 Capital Asset Pricing Model

Building on the work of Harry Markowitz on diversification and modern portfolio theory, Jack Treynor (1962), William Sharpe (1964), John Linter (1965), and Jon Mossin (1996) developed The Capital Asset Pricing Model (CAPM). This model set the foundation for asset pricing that seeks to explain the expected return of an asset predicated on its risk relative to the market. The foundation of the CAPM rests on a series of key assumptions. Firstly, it assumes that investors are rational and risk-averse, making decisions aimed at maximizing their returns for a given level of risk. Secondly, the model assumes a world without taxes and transaction costs, which simplifies the analysis. Additionally, it states that all investors have equal access to information, and they can diversify their portfolios to eradicate unsystematic risk. Lastly the model assumes the existence of a risk-free rate at which investors can lend or borrow an unlimited amount of money. (Perold, 2004)

The CAPM is defined by the following equation:

$$E(R_i) - R_f = \alpha_i + \beta_i \cdot \left[E\left(R_m - R_f\right)\right]$$

1)

Where $E(R_i)$ represents the expected return of the asset, R_f is the risk-free rate, represented by the 1-month US Treasury bill rate. β_i is the beta of the asset depicting its sensitivity to market movements, and $E(R_m)$ is the expected return of the market. Lastly α_i (alpha) represents the portion of an investments return that cannot be explained by the risk associated by the market, a positive alpha means that it has performed better than expected given its beta, and vice versa for a negative alpha. In this equation, beta serves as a measure of systematic risk, indicating the asset's returns sensitivity to the overall market. A beta greater than 1 signifies that the asset is more volatile than the market, while a beta less than 1 indicates a lower volatility. (Fama & French, 2004)

A crucial component of the model is the market risk premium, represented by the term $E\left(R_m - R_f\right)$. This term explains the additional return investors anticipate for bearing the risk of investing in the market over a risk-free asset (Fama & French, 2004). The graphical representation of CAPM is illustrated through the Security Market Line (SML), which demonstrates the relationship between expected return and beta. It aids in deciphering whether an asset is undervalued or overvalued, providing a visual tool for investors. (Black, Jensen, & Scholes, 2006)

Though widely used, CAPM has faced criticisms, particularly regarding its assumptions and empirical validity. These critiques have led to the development of extensions and alternatives to CAPM, such as the Fama-French three-factor model, to address its limitations. Empirical examinations of CAPM have shown mixed results, with some research supporting its predications while others find deviations. As a result, various alternative models have emerged, leading to a vast body of research exploring factors influencing asset returns. (Fama & French, 2004) (Black, Jensen, & Scholes, 2006)

3.3.2 Fama-French models

As previously mentioned, the Fama-French model emerged as an extension to the CAPM model, which was primarily developed to address the limitations of CAPM in explaining stock returns. Through their model, Fama & French (1993) introduced two additional factors that they believed were instrumental in better capturing the variations observed in the stock market, this model is called the Fama-French Three-Factor Model.

The model is mathematically expressed as:

$$E(R_i) - R_f = \alpha_i + \beta_m \cdot \left[E\left(R_m - R_f\right)\right] + s_i \cdot SMB + h_i \cdot HML$$

2)

In this equation $E(R_i)$ denotes the expected return on the asset, R_f is the risk-free rate, represented by the 1-month US Treasury bill rate. β_m represents the market beta (systematic risk) of the asset, $E(R_m)$ is the expected market return, s_i and h_i are the size and value factor of the asset, respectively. The factors SMB (Small Minus Big) and HML (High Minus Low) represent the historic excess return of small-cap companies over large-cap companies, and the historic excess return of value stocks over growth stocks, respectively (Fama & French, 1993).

Lastly, α_i (alpha) represents the excess return of the asset that is not explained by the risk factors in the model.

Fama & French (1993) stated that the size of the company and its book-to-market value were significant determinants in predicting stock returns. They also argued that small-cap and value stocks tend to offer higher expected returns due to their higher inherent risk. Over the years, substantial empirical evidence has supported this model, showing that it explains a significant portion of the variation in stock returns, and thereby outperforming the traditional CAPM model. (Petkova, 2006) (Lettau & Ludvigson, 2001).

However, this model is not without criticism. Some argue that it still might not capture all relevant risk factors. This led to the development of further models like the Carhart Four-Factor Model (Carhart, 1997), which added a momentum factor, and the Fama-French Five-Factor Model, which introduced two more factors: profitability and investment (Fama & French, 2015). The updated Fama-French Five-Factor model is expressed as:

$$E(R_i) - R_f = \alpha_i + \beta_m \cdot \left[E\left(R_m - R_f\right)\right] + s_i \cdot SMB + h_i \cdot HML + r_i \cdot RMW + c_i \cdot CMA$$

3)

Where RMW (Robust Minus Weak) is the probability factor, representing the difference between the returns of firms with robust and weak profitability, and CMA (Conservative Minus Aggressive) is the investment factor, representing the difference between the returns of firms with conservative and aggressive investment policies. Alpha has the same explanation as under the three-factor model, where it represents the excess return of the asset that is not explained by the risk factors in the model.

Lastly, the six-factor model combined the Fama-French Five-Factor model and the momentum factor from the Carhart's four factor model, and is expressed as:

$$E(R_i) - R_f = \alpha_i + \beta_m \cdot \left[E\left(R_m - R_f\right)\right] + s_i \cdot SMB + h_i \cdot HML + r_i \cdot RMW + c_i \cdot CMA + m_i \cdot MOM$$

4)

To summarize, the theoretical framework of the Fama-French models consists of a comprehensive mix of economic principles, empirical evidence, and their practical application in the financial markets. As the model has advanced from its original three-factor to now a six-factor model, it remains a robust framework for dissecting the intricacies of risk elements that influence the financial markets.

3.3.3 q-Factor Model

The q-Factor model is an asset pricing model that has been crafted with an investment-centric lens, developed by Hou, Xue & Zhang (2015). The model was developed as an attempt to capture some of the anomalies that the Fama-French Three-Factor Model failed to account for. The q-Factor model aims to explain the variance in stock returns based on firms' investment and profitability characteristics. The shaping of this model is rooted in the notion that the expected returns on stocks are significantly influenced by the investment and profitability aspect of firms. (Hou, Xue, & Zhang, 2015)

The q-Factor model is represented by four primary factors, which includes market, size, investment, and profitability dimensions. The market factor is a value-weighted return of all stocks on the NYSE, Amex, and Nasdaq, minus the risk-free rate, represented by the 1-month US Treasury bill rate. Investment-to-assets (IA) is the annual change in total assets divided by the prior year's total assets. Profitability is measured as return on equity (ROE), calculated as income before extraordinary items divided by one-quarter-lagged book equity. (Hou, Xue, & Zhang, 2015)

For factor construction, stocks are sorted annually into two size groups, and three groups each for IA and ROE, based on NYSE breakpoints. The sorting into groups is done to ensure that investment and ROE factors are orthogonal to each other. Portfolio returns are calculated on a value-weighted monthly basis, with rebalancing done monthly for ROE and annually for size and IA in June. The size factor is the difference in returns between small and big stocks. The investment factor is the difference between low and high IA portfolio returns. The profitability factor is the difference in returns between low and high ROE portfolios. These factors are computed by averaging the returns of portfolios falling into corresponding categories. (Hou, Xue, & Zhang, 2023).

In a later study, Hoe, Mo, Zue & Zhang (2021) introduced the expected growth factor (EG) to the q-factor model. The expected growth factor is constructed using predictive models for one-year-ahead changes in a firm's investment-to-assets ratio, and is using inputs such as Tobin's q, operating cash flows and changes in return on equity. The factor is then derived each month as the difference between the simple averages of the returns the portfolios with high and low expected investment-to-assets changes. This factor aims to capture the common variations related to the market's expectations of firm growth, as indicated by their investment patterns relative to assets. This addition increased the capability of the q-factor model to predict returns of an asset. Mathematically, the q-Factor model is expressed as:

$$E(R_i) - R_f = \alpha_i + \beta_m \cdot \left[E\left(R_m - R_f\right)\right] + \beta_{ME} \cdot ME + \beta_{IA} \cdot IA + \beta_{ROE} \cdot ROE + \beta_{EG} \cdot EG$$

5)

Where $E(R_i)$ is the expected return of asset i, R_f is the risk-free rate, $E(R_m)$ is the expected return of the market, and ME, IA, ROE, and EG are the size, investment, profitability, and expected growth factors respectively. Alpha (α_i) captures the excess returns that is not explained by the risk factors of the model. Empirical tests and examinations have provided evidence that the q-Factor model explains a significant portion of the cross-sectional variation in expected stock return. In addition, it has found to outperform models such as the Fama-French and Carhart factor models in explaining anomalies. (Hou, Xue, & Zhang, 2015)

3.3.4 Stambaugh-Yuan model

The Stambaugh-Yuan model, introduced by Robert Stambaugh and Yu Yuan in 2017, is a newer four-factor model in the landscape of asset pricing. This model is known primarily for incorporating two "mispricing" factors alongside the conventional market and size factors. This model aims to offer a more robust framework that can better accommodate a wide array of anomalies observed in asset pricing, compared to some of the well-recognized four- and five-factor models. (Stambaugh & Yuan, 2017)

The development and basis of the Stambaugh-Yuan model is rooted in extending the existing asset pricing models. The model introduces "mispricing" factors to fill the gaps that traditional factors might not fully cover, thereby explaining a broader set of anomalies in asset pricing.

The core of this model comprises of four factors. The market factor, representing the comprehensive market risk associated with assets, and the size factor, representing the risk associated with the size of the firms (Stambaugh & Yuan, Mispricing Factors, 2017). Additionally, the model introduces two mispricing factors, MGMT (Management) and PERF (Performance), the two factors are derived from 11 anomalies[2] that are grouped into two clusters, where each cluster contains the anomalies most similar to each other. MGMT[3] contains various investment measures while PERF[4] contains profitability measures (Hou, Mo, Xue, & Zhang, 2019). The two factors are closely related to investor sentiment and is specifically designed to capture the mispricing observed in assets returns (Stambaugh & Yuan, 2017).

The process of deriving the mispricing factors begins each month with the evaluation and ranking of stocks according to the anomaly measures. These rankings are then averaged within two distinct groups, resulting in the creation of two composite measures for each stock, termed P1 and P2. Following this, a 2 x 3 sorting procedure similar to Fama & French (1993 & 2015) and Hou, Zue & Zhang (2015). Each month, stocks[5] from the NYSE, AMEX, and NASDAQ are divided into two groups based on market capitalization, using the NYSE median as a breakpoint. Independently, stocks are then sorted by their P1 and P2 values into three subgroups each, using the 20th and 80th percentile breakpoints of the combined stock universe of NYSE, AMEX, and NASDAQ. (Stambaugh & Yuan, 2017)

The mispricing factors, MGMT and PERF, are then constructed. MGMT is derived from the P1 measures by calculating value-weighted returns of portfolios at the intersection of size and P1 rankings, focusing on the differential between overpriced and underpriced stocks. A similar process using P2 rankings is employed to construct the PERF factor. (Stambaugh & Yuan, 2017)

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[2] The anomalies are net stock issues, composite equity issues, accruals, net operating assets, asset growth, investment-to-assets, distress, O-score, momentum, gross profitability, and return on assets.

[3] MGMT contains; net stock issues, composite equity issues, accruals, net operating assets, asset growth, and investment-to-assets.

[4] PERF contains; distress, O-score, momentum, gross profitability, and return on assets.

[5] Excluding stocks under $5

4. Data

In this section, we provide an overview of the data sources we utilize, and the procedural steps undertaken to ensure robustness of our equity duration estimates. We will outline the origin of our stock return, balance sheet, and factor data. We will also outline the data cleaning measures we have implemented.

We have chosen to limit our dataset to observations between 1970-2022. We have excluded data prior to 1963 due to a significant reduction in the number of firms with reliable data. We then chose to further limit our data to observations after 1970 due to the availability of q-factor model data.

4.1 Data sources

We use monthly stock return data and annual balance sheet data of firms listed on the NYSE, Amex, and Nasdaq when estimating equity duration. Monthly stock return data is sourced from the Center of Research in Security Prices (CRSP) (WRDS, 2023a). We then used the "CRSP/Compustat Merged – Fundamentals Annual" database to merge monthly stock return data with annual Compustat balance sheet data (WRDS, 2023b)

For the benchmarking models we use to assess our portfolio returns, we retrieved monthly return data on the five Fama-French factors and momentum factor from Kennneth French's Data Library (French, 2023). We obtained the monthly factor returns of the q-factor model from the Hou-Xue-Zhang q-factors data library (Hou, Xue, & Zhang, 2023b). Monthly Staumbaugh and Yuan factor data was obtained from Robert F. Stambaugh's website (Stambaugh, 2023).

4.2 Data cleaning

Our data cleaning procedures are heavily influenced by Weber (2018). Following standard conventions and to keep consistent with Weber (2018), we start off by excluding financial firms (SIC codes 6000-7000) and utility companies (SIC codes 4900-5000). We also exclude firms with less than 2 years of observations.

We then move on to attempt to correct the delisting bias in CRSP data showcased by Shumway (1997). Shumway found that firms which were delisted unexpectedly due to performance reasons, e.g., bankruptcy, often had missing delisting returns. If we fail to account for these missing delisting returns, we could run the risk of introducing an upward bias in our stock return data. To account for this bias, we follow the recommendation in Schumway (1997). We assume a delisting return of -30% in cases where delisting returns are missing, and firms are delisted due to performance reasons (delisting codes 400-591).

There are instances where CRSP report delisting reports several months after the stock ceased trading. In these cases, we chose the same approach as Cohen et al. (2009) and spread the delisting returns evenly across the months between delisting and the reporting of delisting returns. We chose this approach because the stock may continue to trade over-the-counter, and the delayed delisting return may reflect several months of price movements. This could overstate the monthly price movements.

4.3 Variable definitions

In this subsection, we will define the CRSP/Compustat variables we use to estimate equity duration later in our paper.

We define the book value of equity (BE) as the sum of total stockholders' equity (TEQ), deferred taxes and investment tax credit, minus the book value of preferred stock (Davis, Fama, & French, 2000). The reasoning behind subtracting the book value of preferred stock, is that the U.S. CRSP stock database excludes preferred shares (Wharton, 2023). This adjustment ensures a like-for-like comparison when utilizing merged CRSP/Compustat data. If TEQ is missing, we define BE as total common equity (CEQ). If both TEQ and CEQ are missing, we define BE as the difference between total assets and total liabilities (Davis, Fama, & French, 2000).

Next, we define return on equity (ROE) as net income before extraordinary items (NI) over lagged BE. We omit extraordinary items from our analysis because theoretically they do not represent the fundamental operational performance. By excluding these items, we aim to enhance the accuracy of our forecasts for Return on Equity (ROE), as suggested by Fairfield, Sweeney & Yohn (1996).

5. Methodology

In this section, we aim to provide a clear and straightforward explanation of how we approached each phase of our study. We will start off by giving an overview of we manage and benchmark our portfolios. We then delve into more detail on how we forecast cash flows and estimate implied equity duration.

5.1 Portfolio management and benchmarking

At the end of every June, starting in 1970, and ending in 2022, we estimate the cash flow duration of every firm in our merged CRSP/Compustat dataset. Based on our duration estimates, we then organize the stocks of these firms into value-weighted decile portfolios. That is, portfolio 1 (Pf1) comprises stocks of the firms in the bottom 10% cash flow duration, while portfolio 10 (Pf10) includes those in the top 10%. The weight of each stock is the ratio of the individual firm's market capitalization. Each stock's weight is determined by dividing its market capitalization, calculated as the number of shares outstanding multiplied by the current share price, by the collective market capitalization of all firms within the same decile portfolio.

We chose value-weighted portfolios instead of equal-weighted portfolios to limit the effects of firms with low market capitalization. While these firms account for a small portion of the aggregate market capitalization, they represent the majority of individual stocks in our sample. Using equal weights would then overweight these "microcap" firms, leading to a less accurate representation of the stock market (Hou, Xue, & Zhang, 2018).

Having constructed the decile portfolios, we are set to deploy our long-short-duration trading strategy. Annually, at the end of June, we take a long position in the portfolio of the shortest duration stocks (Pf1) and a short position in the highest duration stock portfolio (Pf10). These positions are maintained until the subsequent June, at which point we update Pf1 and Pf10. After implementing our strategy from 1970 to 2022, we benchmark our monthly portfolio returns against factor models.

5.2 Computing implied equity duration

When calculating implied equity duration, we use the Macaulay duration as our base, a topic we discussed in section 3.1. Recall from that section that the Macaulay duration gives us the weighted average time it takes to receive a bond's fixed cash flows. This duration takes into account the present value of each cash flow compared to the total value of the bond.

The equation for Macaulay duration is:

$$Dur_{i,t} = \frac{\sum_{s=1}^{T}\left[s \cdot \frac{CF_{i,t+s}}{(1+r)^s}\right]}{P_{i,t}}$$

6)

But to determine the implied equity duration, we must adjust our approach. Two main issues arise: First, we do not know when and how much cash equity investors will receive. Second, unlike bonds, equities do not typically have a set lifespan. To handle the unpredictability of cash flows, we use forecasting techniques, which we will delve into in the section 5.3. In this section, we focus on how to modify the Macaulay duration formula for assets without a definite lifespan. There are also several other ways of computing equity duration, detailed in Appendix 1: Ways of computing equity duration.

Dechow et al. (2004) shows that the formula for Macaulay duration can be split into a definite forecasting period and a terminal value, as demonstrated in equation 7). While this equation may initially appear complex, the equation becomes more intuitive when we apply the assumptions detailed later, which allow us to simplify equation 7) into equation 9).

$$Dur_{i,t} = \frac{\sum_{s=1}^{T}\left[s \cdot \frac{CF_{i,t+s}}{(1+r)^s}\right]}{\sum_{s=1}^{T}\left[\frac{CF_{i,t+s}}{(1+r)^s}\right]} \cdot \frac{\sum_{s=1}^{T}\left[\frac{CF_{i,t+s}}{(1+r)^s}\right]}{P_{i,t}} + \frac{\sum_{s=T+1}^{\infty}\left[s \cdot \frac{CF_{i,t+s}}{(1+r)^s}\right]}{\sum_{s=T+1}^{\infty}\left[\frac{CF_{i,t+s}}{(1+r)^s}\right]} \cdot \frac{\sum_{s=T+1}^{\infty}\left[\frac{CF_{i,t+s}}{(1+r)^s}\right]}{P_{i,t}}$$

7)

There are some key differences in the interpretation of the variables in equation 7) and the standard Macaulay duration formula. $CF_{i,t}$, denotes the net cash flows to equity holders, hereby called cash flows, of firm i at time t (1970-2022). $P_{i,t}$ denotes the market capitalization of equity of firm i at time t, which is the product of share price times number of shares outstanding. The discount rate is denoted by r, and is held constant across both i and t. This may seem like a heroic assumption. When looking at the duration formula, firm specific discount rates would affect $Dur_{i,t}$. This could also affect the relative ranking of firms' implied equity duration, a crucial component of our research. There is, however, evidence that long-term (10 years) discount rates do not vary across firms, lending credibility to our assumption (Keloharjua, Linnainmaa, & Nyberga, 2020).

We compute implied equity duration at time t, so the s represents the number of years in the future. As we will see in section 5.3, we use a forecasting period of 15 years, which means that $T = 15$. To clarify, the first two terms in equation 7) compute the value-weighted sum of duration in the definite forecasting period of 15 years. The two last terms compute the duration of the infinite terminal cash flows.

Next, we adopt the simplifying assumption from Dechow et al. (2004) and assume that the terminal value of cash flows equals a level perpetuity of cash flows equal to the difference between $P_{i,t}$ and the present value of cash flows in the definite forecasting period. The assumption of level perpetuities hinges on the definite forecasting period being long enough to account for firm- and industry specific growth opportunities (Weber, 2018). We will cover this in more detail in section 5.3.

Given level perpetuities, we find it reasonable to assume that the rest of the above assumption holds. This is due to the dividend discount model stating that $P_{i,t}$ is equal to the present value of all future cash flows to equity holders (Williams, 1938). Thus, the present value of the terminal value of cash flows can be expressed as follows:

$$\sum_{s=T+1}^{\infty}\left[\frac{CF_{i,t+s}}{(1+r)^s}\right] = \left(P_{i,t} - \sum_{s=1}^{T}\left[\frac{CF_{i,t+s}}{(1+r)^s}\right]\right) \qquad 8)$$

The assumption above allows us to substitute the right-hand-side of equation 8) into equation 7), allowing us to simplify equation 7) in the following manner (Dechow, Sloan, & Soliman, 2004):

$$Dur_{i,t} = \frac{\sum_{s=1}^{T}\left[s \cdot \frac{CF_{i,t+s}}{(1+r)^s}\right]}{P_{i,t}} + \left(T + \frac{1+r}{r}\right) \cdot \frac{P_{i,t} - \sum_{s=1}^{T}\left[\frac{CF_{i,t+s}}{(1+r)^s}\right]}{P_{i,t}}$$

9)

We have now explained how we compute the implied equity duration of a firm. In the following section, we will showcase how we forecast $CF_{i,t}$.

5.3 Forecasting cash flows

Before computing the implied equity duration of a firm, we first need to forecast its future cash flows. To avoid confusion, we remind the reader that when we refer to the net cash flows to equity holders as "cash flows". The cash flows of a given firm can be expressed as follows (Dechow, Sloan, & Soliman, 2004):

$$\begin{aligned} CF_{i,t+s} &= NI_{i,t+s} - \left(BE_{i,t+s} - BE_{i,t+s-1}\right) \\ &= BE_{i,t+s-1} \cdot \left[\frac{NI_{i,t+s}}{BE_{i,t+s-1}} - \frac{BE_{i,t+s} - BE_{i,t+s-1}}{BE_{i,t+s-1}}\right] \\ &= BE_{i,t+s-1} \cdot \left(ROE_{i,t+s} - BE_{i,t+s}^{growth}\right) \end{aligned}$$

10)

The variable $CF_{i,t+s}$ denotes the cash flows of firm i at time t, s years into the future. $NI_{i,t+s}$ is net income before extraordinary items[6], hereby referred to as net income, and $BE_{i,t+s}$ is the

[6] To better forecast ROE over a fifteen-year horizon, we exclude extraordinary items from net income, as their one-off nature may distort predictions of a firm's ongoing profitability (Fairfield, Sweeney, & Yohn, 1996).

book value of equity. The cash flows are thus defined as the difference between net income before extraordinary items and the change in book value of equity from the year prior. This is equivalent to the product of lagged book equity value and the difference between ROE and BE-growth, which are the variables we forecast.

In our forecasting methodology, we employ the framework outlined in Weber (2018). Return of equity (ROE) and book equity growth (BE-growth) are modelled as mean-reverting processes. Specifically, we treat these variables as first-order autoregressive (AR(1)) processes that gravitate towards their respective long-term means of 12% for ROE and 6% for BE-growth. The reversion parameters dictate the speed and extent to which ROE and BE-growth revert to their means. Both parameters are held constant across all firms and over time, reflecting a uniform reversion tendency.

We forecast future ROE using its historical data, accounting for its mean-reverting characteristic. For BE-growth predictions, we utilize past sales growth, which Nissim & Penman (2001) suggests is a more accurate predictor of BE-growth. Thus, we incorporate the mean reversion parameter of sales growth, ρ, into our model. The models are denoted as follows:

$$ROE_{i,t} = \mu + \lambda \cdot (ROE_{i,t-1} - \mu) \tag{11}$$

$$BE_{i,t}^{growth} = \tau + \rho \cdot (BE_{i,t-1}^{growth} - \tau) \tag{12}$$

Here, μ and τ are the long term means of ROE and BE, while λ and ρ are the estimated mean reversion parameters of ROE and sales growth. We estimate mean reversion parameters of 0,62 and 0,25 for ROE and sales growth, respectively. Keep in mind that we use the mean reversion parameter of sales growth when forecasting BE-growth.

Now that the models have been fitted, we forecast both ROE and BE-growth 15 years ahead. We ensured that 15 years was a sufficiently long time period for all estimates of ROE and BE-growth having mean reverted. This is especially important as we are computing perpetuities. It seems entirely unrealistic that a firm will have higher than average ROE and BE-growth in perpetuity.

After having forecast ROE and BE-growth 15 years ahead for all the firms in our sample, we use these results to compute cash flows following equation 10). We now have all the inputs necessary to start computing implied equity duration and start building our portfolios and analyze our results.

6. Results

In this section, we present our findings on the short duration premium from 1970 to 2022. Our first step is to summarize the data. This sets the stage for the analysis that follows. We will then examine the factors that contribute to the premium.

6.1 Descriptive data

Before analyzing and presenting our results, we will present some descriptive data. The table below showcases firm-level data of every third year in our sample period of 1970-2022. We see that the number of firms each year varies between 894 and 2521, which is quite a large span. The main source of differences from one year to the next, are variations in the number of verified links between the CRSP and Compustat databases. We are however confident that we have a sufficient number of unique firms every year in our sample for all of our 10 decile portfolios to be sufficiently diversified. This is an important consideration. We want to make sure that the portfolio returns represent the returns of stocks with increasing implied equity durations, instead of random firm-specific variations.

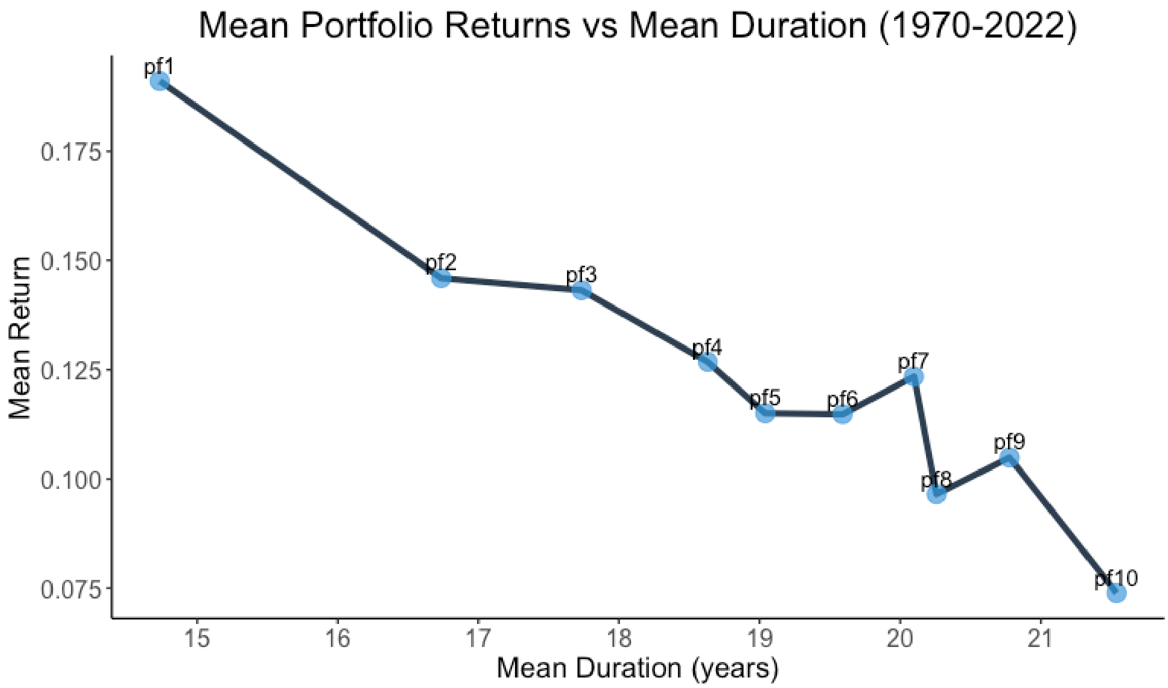
When looking at Table 1, we see that the distribution of the sample firms' implied equity durations, we first notice that the average and median (q50%) durations are relatively closely grouped, indicating stable estimates of implied equity duration. This is further illustrated by the first and ninth decile thresholds, q10% and q90%, which are thresholds for the bottom and top 10% of the distribution of implied equity duration for any given year. It is no surprise that we observe relatively stable estimates of implied equity durations. Recall from section 5.3 where we assumed that ROE and BE-growth mean revert to their respective long-run means.

Table 1: This table contains an overview of firm-level data for every third year of our sample period of 1970-2022. The table lists the number of unique firms in our sample, mean monthly return, weight, and duration for each individual stock during a given year. The quantiles are computed using the sorted distributions of implied equity durations, where q10% represents the threshold value for the first decile, q50% denotes the median, and q90% marks the threshold value for the ninth decile.

Year	# Firms in sample	Mean. M. Return	Mean. Weight	Mean. Duration	q10%	q50% (median)	q90%
1970	894	0.01%	0.012	16.31	9.38	17.25	21.59
1973	1108	-0.01%	0.010	15.40	8.09	16.03	21.68
1976	1729	0.01%	0.006	13.15	5.55	13.48	20.16
1979	1789	0.02%	0.006	13.73	7.21	14.05	19.71
1982	1622	0.01%	0.007	14.23	6.99	14.68	20.68
1985	1651	0.01%	0.007	17.23	12.35	17.39	21.99
1988	1699	0.01%	0.007	18.88	14.49	19.12	23.22
1991	1785	0.01%	0.006	17.96	11.68	18.62	23.14
1994	1932	0.00%	0.006	19.06	14.03	19.73	23.40
1997	2385	0.01%	0.005	19.55	14.59	20.23	23.80
2000	2521	0.00%	0.005	18.68	11.41	19.74	24.10
2003	2336	0.01%	0.005	19.23	13.07	20.03	24.16
2006	2187	0.01%	0.005	20.13	16.30	20.58	23.84
2009	2007	0.02%	0.006	18.68	12.21	19.41	24.05
2012	1927	0.01%	0.006	19.11	13.90	19.77	23.61
2015	1940	0.00%	0.006	19.99	15.51	20.65	23.88
2018	1892	0.00%	0.006	20.28	15.24	20.96	24.40
2021	1883	0.01%	0.007	19.88	13.33	21.14	24.62

After having done all the necessary forecasting and computations, we form our 10 portfolios based on calculated duration. Pf1 are a selection of the stocks with the 10% lowest duration, while Pf10 consists of the stocks with the 10% highest duration. We then value-weight our portfolios as shown in section 5.1. If we look at Figure 1, we can see that there appears to be a clear trend where average annual portfolio returns seem to decrease as the average duration of the portfolios increase. This is an interesting observation, as it seems to be fully in line with our expectations of there being a short duration premium in the stock market.

Figure 1: This figure depicts the simple annual portfolio returns of portfolios 1 through 10 plotted against average portfolio durations. We categorize common stocks listed on NYSE, Amex, and Nasdaq into deciles by duration at the end of each June from 1970 to 2022. Portfolio returns and durations are value weighted.



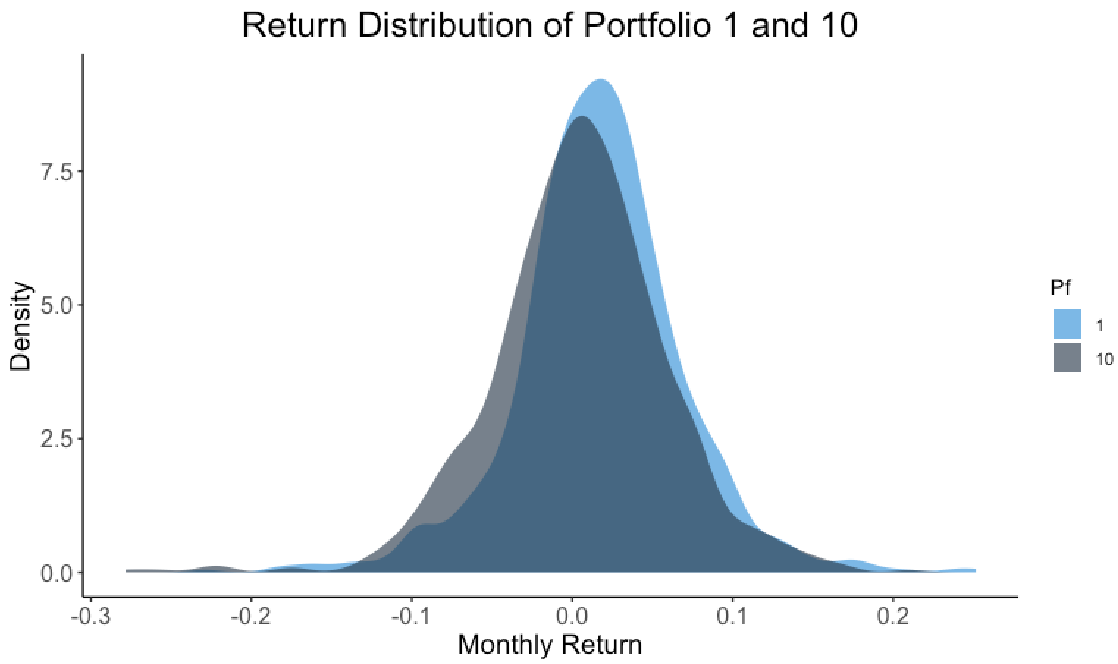
Let us pause to clarify the concept of a "short duration premium". To do so, we will quickly revisit the differences between implied equity duration and traditional bond duration. A critical distinction to underline is that equity cash flows are uncertain in both timing and amount, unlike bond cash flows, which are predetermined. For the sake if illustration, let us come with a highly stylized example. Suppose firm A and B are identical except for the structure of their cash flows. Every year, they have an equal probability of generating "high" and "low" cash flows. Firm A will generate all its future cash flows sometime during the next year, while firm B does so over the next 5 years. Firm A has an equal probability of generating cash flows of either 1000 or 0. Now suppose that Firm B has an equal probability of generating either 200 or 0 each year during the next 5 years. The expected values of each firms' cash flows are equal, assuming no discounting. A risk-neutral investor would be indifferent between the two, but assuming investors are risk averse, holding all else equal, the investors would choose to invest in the less risky option, Firm B. Therefore, Firm A, the riskier firm, would have to offer higher compensation in the form of higher returns.

Table 2: This table summarizes the mean monthly excess returns ($\overline{R_p}$), calculated as portfolio returns minus the 1-month US treasury bill rate. It also includes the standard deviations of the excess returns (σ_p). Additionally, the table reports the mean monthly Sharpe ratios ($\overline{SR}$) for the ten decile portfolio and the long-short-duration portfolio (SML) from 1970 to 2022. Note that $\overline{SR}$ differs from the quotient of $\overline{R_p}$ and σ_p because they are ratios, not direct calculations.

	Pf1	Pf2	Pf3	Pf4	Pf5	Pf6	Pf7	Pf8	Pf9	Pf10	SML
						1970-2022					
$\overline{R_p}$	1.12%	0.84%	0.75%	0.56%	0.52%	0.48%	0.63%	0.55%	0.36%	0.32%	0.57%
σ_p	4.70%	4.69%	4.62%	4.82%	4.83%	4.78%	4.90%	5.07%	4.97%	5.38%	4.25%
$\overline{SR}$	0.26	0.22	0.17	0.13	0.15	0.13	0.14	0.12	0.11	0.07	0.16
						1970-1980					
$\overline{R_p}$	1.23%	0.58%	0.77%	0.15%	0.35%	0.22%	0.03%	-0.03%	-0.46%	0.23%	1.00%
σ_p	5.67%	5.38%	4.94%	5.60%	5.33%	5.46%	5.53%	5.71%	5.83%	6.25%	5.67%
$\overline{SR}$	0.22	0.13	0.13	-0.02	0.02	0.00	-0.07	-0.1	-0.13	-0.03	0.18
						1980-1990					
$\overline{R_p}$	0.94%	0.84%	0.49%	0.48%	0.58%	0.37%	0.52%	0.33%	0.14%	0.15%	0.79%
σ_p	4.33%	4.93%	4.94%	5.36%	5.70%	5.37%	6.12%	6.14%	6.15%	6.33%	4.60%
$\overline{SR}$	0.17	0.19	0.10	0.09	0.15	0.10	0.10	0.06	0.05	0.05	0.14
						1990-2000					
$\overline{R_p}$	1.33%	1.29%	0.79%	0.78%	1.07%	0.78%	1.03%	0.76%	0.82%	0.42%	0.91%
σ_p	4.35%	3.66%	4.44%	3.89%	3.89%	4.06%	3.88%	4.17%	3.89%	4.33%	3.51%
$\overline{SR}$	0.35	0.42	0.18	0.22	0.31	0.23	0.31	0.21	0.22	0.13	0.25
						2000-2010					
$\overline{R_p}$	0.95%	0.76%	0.66%	0.53%	0.09%	0.37%	0.58%	0.64%	0.33%	0.18%	0.77%
σ_p	5.11%	4.95%	4.77%	4.78%	5.07%	4.81%	5.01%	5.11%	4.98%	5.48%	3.71%
$\overline{SR}$	0.24	0.19	0.15	0.12	0.08	0.12	0.12	0.18	0.09	0.03	0.19
						2010-2022					
$\overline{R_p}$	1.09%	0.78%	0.95%	0.81%	0.69%	0.80%	1.04%	1.03%	0.81%	0.62%	0.47%
σ_p	4.24%	4.65%	4.26%	4.65%	4.37%	4.53%	4.46%	4.67%	4.66%	4.97%	3.23%
$\overline{SR}$	0.27	0.16	0.26	0.21	0.19	0.18	0.22	0.23	0.23	0.15	0.14

When looking at table 2, it does not seem to lend any credibility to our previous conjecture. We stated that the high mean returns seen in short-duration stocks could simply be compensation for increased risk. The table presents a comprehensive summary that included the mean monthly excess returns ($\overline{R_p}$), the standard deviations (σ_p), and the mean monthly Sharpe ratios ($\overline{SR}$) for our ten decile portfolios. Additionally, it details the same metrics for our long-short-duration portfolio (SML). These statistics are provided for different time periods, giving us insights into the performance dynamics and risk-adjusted returns of these portfolios over time. The inclusion of rolling standard deviations offers a nuanced view of the volatility trends, while the Sharpe ratio enable an assessment of the risk-adjusted performance, allowing for a more informed comparison across different time periods. We observe that Pf1 has consistently outperformed Pf10 in terms of $\overline{R_p}$, while generally being subject to a lower σ_p. This relationship can be further observed by Pf1 having higher $\overline{SR}$ than Pf10.

Figure 2: The figure, with accompanying table, detail the distribution characteristics of the monthly excess returns for Portfolio 1 (Pf1) and Portfolio 10 (Pf10) from 1970 to 2022. Excess returns are defined as simple monthly returns, minus the 1-month US treasury bill rate. The density curves represent the distribution frequency of returns, while the table quantifies the skewness and kurtosis of each portfolio, providing a statistical summary of the distributions. Skewness measures the asymmetry of the return distribution relative to the normal distribution. Kurtosis reflects the "tailedness" of the distribution.



	Pf1	Pf10
Skewness	-0.19	-0.32
Kurtosis	5.40	5.37

The figure above plots the distribution of monthly simple returns of Pf1 and Pf10 between 1970-2022. When inspecting the distribution, along with the skewness and kurtosis in Figure 2, we see that the return distributions of the two portfolios are relatively similar. However, Pf10 has historically been prone to more negative return shocks than Pf1. Weber (2018) found that firms with high implied equity duration tend to face more frequent negative earnings surprises and seem to engage in a higher degree of earnings management than firms with low implied equity duration. Could this mean that the short duration premium we observe in Figure 1 can be explained by short duration stock facing fewer negative shocks than long duration stocks?

We cannot yet draw any general conclusions regarding the supposed short equity duration premium. In the following sections, we will use factor models to try to assess whether this premium really exists, and if so, how large it is and what it is comprised of.

6.2 Factor models

In this section, we will start off by attempting to explain the short duration premium using the traditional CAPM-model, before moving on to more advanced factor models. We have run regressions on all 10 decile portfolios (Pf1-Pf10) and the short-minus-long (SML) portfolio. A quick reminder, Pf1 is the portfolio with the lowest implied equity duration, Pf10 is the one with the highest, and the ones in between are of increasing duration. Portfolio SML is a long position in Pf1 and a short position in Pf10.

One of the issues we can encounter when running numerous factor models to try to break down the short duration premium, is factor fishing. Factor fishing, also referred to as "factor zoo", is a term used to describe the practice of shifting through large amounts of financial data to find variables that appear to predict stock returns, leading to the identification of numerous "factors". However, many of these factors may be the result of data mining or statistical anomalies, rather than having a genuine economic rationale or predictive power.

To address this issue, we could attempt to ensure the robustness of the factors by requiring a higher level of statistical significance, such as a 1% significance level, rather than the more common 5%. Another approach could be to set a higher criterion for the t-statistic, as a higher t-statistic can provide greater confidence in the factor's reliability. A t-stat of 3 or above is used by Harvey, Liu and Zhu (2016) for a new factor to be considered to have a statistical significance.

Going forward when evaluating the robustness of factor models, our approach to statistical significance will adapt to the nuances of different models. For traditional factor models, such as the CAPM and Fama-French models, we will uphold a 5% significance level threshold for the risk factors. Moving from the traditional models to the more contemporary ones, such as the q-factor and the Stambaugh-Yuan model, we will employ a more rigorous standard. Following the insights of Harvey et al. (2016), we will employ a t-statistic threshold of 3 for these newly introduced factors to be deemed statistically significant. This higher t-statistic requirement recognizes that while the factors are grounded in theoretical principles, and might justify a lower t-statistic, we must ensure the credibility and reliability of factors that emerge from empirical investigation. This policy aims to strengthen our factor model's validity and statistical significance.

6.2.1 Fama-French 3-factor

The Fama-French 3-factor model results in the table below, are an extension of the CAPM-results presented in Appendix 2: CAPM regression results. What sets this model apart from the CAPM, is the introduction of the explanatory variables SMB and HML. A quick reminder from section 3.3.2: SMB is the return of a well-diversified portfolio of small-cap-stocks, minus one comprised of big-cap-stock. The same goes for HML, just that the two portfolios are comprised of high-and low book-to-market (BM) stocks.

Table 3: The table displays Fama-French 3-factor model regression results. The dependent variable is monthly excess market returns $(R_i - R_f)$. Market coefficient $(R_m - R_f)$, small-minus-big (SMB), high-minus-low (HML), and alpha (α) are reported for each portfolio and the long-short-duration (SML) portfolio. The table also reports number of observations, R-squared. Adjusted R-squared, residual standard error, and F-statistics. We categorize common stocks listed on NYSE, Amex, and Nasdaq into deciles by duration at the end of each June from 1970 to 2022. Portfolio returns and durations are value weighted.

	Dependent variable:										
	Monthly Excess Portfolio Returns 1970-2022										
	Pf1	Pf2	Pf3	Pf4	Pf5	Pf6	Pf7	Pf8	Pf9	Pf10	SML
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
α	0.495***	0.188**	0.147*	-0.047	-0.091	-0.085	0.060	-0.004	-0.191*	-0.246*	0.741***
	t = 4.645	t = 1.972	t = 1.819	t = -0.524	t = -0.872	t = -0.912	t = 0.615	t = -0.039	t = -1.790	t = -1.908	t = 4.366
$R_m - R_f$	0.919***	0.988***	0.985***	1.009***	1.062***	1.024***	1.025***	1.042***	1.033***	1.071***	-0.152***
	t = 28.820	t = 36.503	t = 42.859	t = 37.659	t = 35.083	t = 36.614	t = 34.179	t = 41.191	t = 34.216	t = 29.074	t = -3.003
SMB	0.222***	0.118***	-0.006	0.043	-0.080*	-0.102**	-0.031	0.021	-0.102**	-0.014	0.236***
	t = 5.189	t = 3.334	t = -0.185	t = 1.067	t = -1.923	t = -2.403	t = -0.660	t = 0.491	t = -2.072	t = -0.236	t = 2.911
HML	0.216***	0.206***	0.118***	0.062	0.056	0.001	-0.040	-0.143***	-0.059	-0.130**	0.346***
	t = 4.874	t = 4.910	t = 3.041	t = 1.369	t = 1.162	t = 0.016	t = -0.895	t = -3.182	t = -1.425	t = -2.547	t = 5.279
Observations	636	636	636	636	636	636	636	636	636	636	636
R^2	0.741	0.800	0.826	0.810	0.791	0.801	0.785	0.807	0.772	0.726	0.111
Adjusted R^2	0.740	0.799	0.825	0.809	0.790	0.800	0.784	0.806	0.771	0.725	0.107
Residual Std. Error (df = 632)	2.596	2.292	2.062	2.260	2.484	2.334	2.490	2.429	2.591	3.104	4.174
F Statistic (df = 3; 632)	602.364***	845.000***	1,000.352***	899.996***	795.940***	845.727***	768.767***	878.812***	711.629***	558.943***	26.238***
Note:	*p<0.1; **p<0.05; ***p<0.01										

When looking at the regression results in Table 3, the first thing we observe, is that Pf1 has a highly significant positive HML-coefficient, while Pf10 has a negative coefficient estimate, significant at a 5% significance level. These estimates are in line with our expectations as Weber (2018) found that there seems to be a strong negative correlation between implied equity duration and BM-ratio. The intuition behind this could be related to the fact that firms with high BM-ratios often are dubbed "value-firms", which is often a characteristic of low-duration firms.

The SML-portfolio exhibits an alpha of 0.74%, significant at a 5%-level after introducing the SMB and HML variables. Since the 3-factor model falls into the category of the more "traditional" factor models we refer to in our previous discussion of "factor fishing", we deem the alpha to be statistically significant at conventional levels.

It is noteworthy that the SML portfolio has a significant alpha, even with its relatively high correlation with the HML factor. We expected a larger drop in the alpha after observing approximately 0.90% from the CAPM model, detailed in Appendix 2: CAPM regression results. This persistence suggests the SML portfolio might be influenced by a risk factor that is related to, but not fully encompassed by the HML factor.

The R-squared of the SML-portfolio has risen from 2.9% to 11.1% after controlling for the SMB and HML factors. It is however clear that we still have a long way to go in trying to explain the alpha of the SML-portfolio. We will keep expanding the model in the subsequent sections.

6.2.2 Fama-French 5-factor

We will now expand upon the previous 3-factor model by adding the RMW and CMA-factors. The two additional factors are explained in section 3.3.2. Again, let us take a minute to consider whether the regression results below are in line with economic intuition. We would have expected to see positive CMA-coefficient estimates for Pf1. This is because we would have assumed the returns of Pf1 to be positively correlated with the returns of firms with a conservative reinvestment policy. All things equal, this would suggest that they pay out a larger proportion of their earnings as dividends. We assumed the opposite to hold true for Pf10.

What we observe, is however a slightly different story. First of all, the CMA-coefficient estimate for Pf1 is not statistically significantly different from 0. On the other hand, Pf10 exhibits a positive significant coefficient, which is contrary to what we expected. This implies that Pf10 co-moves with conservative stocks. Contrary to this observation, one would assume that Pf10, comprising of high-duration stocks, would exhibit a closer covariance with stocks with an aggressive investment policy, similar to the behaviour of growth stocks. The CMA-coefficient for the SML-portfolio is not significantly different from 0, indicating that the SML-portfolio is not exposed to the CMA-factor.

Table 4: The table displays Fama-French 5-factor model regression results. The dependent variable is monthly excess market returns $(R_i - R_f)$. Market coefficient $(R_m - R_f)$, small-minus-big (SMB), high-minus-low (HML), robust-minus-weak (RMW), conservative-minus-aggressive (CMA), and alpha (α) are reported for each portfolio and the long-short-duration (SML) portfolio. The table also reports number of observations, R-squared. Adjusted R-squared, residual standard error, and F-statistics. We categorize common stocks listed on NYSE, Amex, and Nasdaq into deciles by duration at the end of each June from 1970 to 2022. Portfolio returns and durations are value weighted.

	Dependent variable:										
	Monthly Excess Portfolio Returns 1970-2022										
	Pf1	Pf2	Pf3	Pf4	Pf5	Pf6	Pf7	Pf8	Pf9	Pf10	SML
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
α	0.530***	0.138	0.093	-0.133	-0.183*	-0.194**	-0.101	-0.106	-0.327***	-0.401***	0.931***
	t = 4.751	t = 1.431	t = 1.140	t = -1.449	t = -1.749	t = -1.972	t = -0.986	t = -1.000	t = -2.977	t = -2.988	t = 5.246
$R_m - R_f$	0.918***	0.997***	0.997***	1.026***	1.076***	1.048***	1.064***	1.062***	1.064***	1.109***	-0.190***
	t = 28.134	t = 36.728	t = 40.157	t = 39.366	t = 36.234	t = 39.147	t = 35.703	t = 41.896	t = 34.908	t = 29.521	t = -3.697
SMB	0.188***	0.149***	0.015	0.085**	-0.021	-0.052	0.033	0.075*	-0.042	0.048	0.140*
	t = 4.196	t = 3.984	t = 0.413	t = 2.091	t = -0.529	t = -1.208	t = 0.679	t = 1.822	t = -0.852	t = 0.876	t = 1.812
HML	0.209***	0.181***	0.073*	0.002	0.016	-0.080	-0.182***	-0.208***	-0.166***	-0.265***	0.474***
	t = 3.474	t = 3.391	t = 1.697	t = 0.031	t = 0.316	t = -1.614	t = -3.452	t = -4.260	t = -3.086	t = -3.970	t = 5.599
RMW	-0.131**	0.118**	0.085*	0.165***	0.227***	0.197***	0.248***	0.210***	0.234***	0.242***	-0.372***
	t = -2.373	t = 2.050	t = 1.677	t = 2.913	t = 3.605	t = 3.446	t = 3.876	t = 3.799	t = 4.008	t = 3.432	t = -4.108
CMA	0.039	0.037	0.092	0.112	0.054	0.154**	0.289***	0.115	0.210***	0.274***	-0.234*
	t = 0.427	t = 0.449	t = 1.191	t = 1.499	t = 0.800	t = 2.141	t = 3.550	t = 1.408	t = 2.649	t = 3.119	t = -1.818
Observations	636	636	636	636	636	636	636	636	636	636	636
R^2	0.744	0.803	0.828	0.815	0.798	0.808	0.798	0.813	0.782	0.736	0.144
Adjusted R^2	0.742	0.801	0.826	0.814	0.797	0.806	0.797	0.812	0.780	0.734	0.137
Residual Std. Error (df = 630)	2.584	2.283	2.055	2.234	2.443	2.295	2.415	2.390	2.538	3.051	4.102
F Statistic (df = 5; 630)	366.369***	512.794***	605.653***	555.863***	498.757***	529.370***	498.396***	548.924***	450.743***	351.993***	21.230***
Note:											*p<0.1; **p<0.05; ***p<0.01

Another thing that may seem strange at first, is the fact that the SML-portfolio has a higher estimated alpha then what we observed using both the CAPM (see Appendix 2: CAPM regression results) and Fama-French 3-factor model. This may seem counterintuitive, as we would expect that adding more factors, would, if anything, decrease the observed alpha.

Most of this increase in alpha can however be explained by a sharp decrease in Pf10's alpha. Keep in mind that SML is simply a long position in Pf1 and a short position in Pf10. Pf10 went from having a non-significant alpha in the 3-factor model to a highly significant alpha of

-0.40%. According to the 5-factor model, Pf10 destroys value to the tune of 0.40% during an average month. Then, by going short in Pf10, we observe an equally large increase in the SML-alpha compared to Pf1.

Looking at the table above, the SML-portfolio has returned an average monthly alpha of 0.93% between 1970 and 2022. We find these results intriguing. We observe an average monthly return of 0.93% that cannot be explained by the 5-factor model. This leads us to believe that the short duration premium may not be explainable by the traditional risk factors found in the 5-factor model. We also tried controlling for the momentum and liquidity factors, which did not do much in terms of explaining the SML-portfolio alpha. The SML-portfolio did however exhibit a slight positive exposure to the liquidity factor, significant at a 5%-level (see Appendix 3: Fama-French 6-factor model + liquidity factor regression results).

While a monthly alpha of 0.93%, accompanied by a t-statistic exceeding 5, might initially appear overly optimistic, it is not unprecedented in financial literature. For instance, Weber (2018) reported a monthly alpha of 1.25% with a t-statistic of 6.58 for his volatility-managed, equal-weighted SML portfolio, benchmarked against the Fama-French 5-factor model from 1963-2013. Weber (2018) does not report factor loadings, so we are only able to compare alphas and t-statistics. While the alphas in Weber (2018) are not directly comparable to the ones we report, the comparison suggests that our results are more conservative than they initially appear.

6.2.3 The q-factor model

In this section, we transition from the traditional Fama-French models to the more contemporary Q-factor model. As previously discussed in section 6.2, we will apply a more stringent standard for statistical significance, requiring that the observed t-statistics exceed an absolute value of 3. To clarify, this elevated significance threshold applies for the IA, ROE, and EG-factors.

When looking back at section 3.3.3, the reader may recognize that the ME, IA, and ROE-factors seem similar to the SML, CMA, and RMW-factors in the Fama-French 5-factor model. Although they may be similar, there are some important differences we should be aware of. The size factors (ME and SML) are conceptually similar but differ slightly in portfolio construction methods. The same goes for the investment factors (IA and CMA). Lastly, the profitablility factors (ROE and RMW) differ more from one another. The RMW factor in the Fama-French model is based upon operating profitability, while the ROE factor, just as the name implies, is based upon return on equity (Hou, Xue, & Zhang, 2023) (Fama & French, 2015).

We still see a large, highly significant alpha of almost 1% for the SML-portfolio. The model continues to demonstrate negative market exposure for the SML-portfolio, consistent with findings from our previous Fama-French model analyses. Beyond this, ROE emerges as the only coefficient estimate that attains statistical significance, displaying negative exposure to the ROE factor. Although we observe a positive correlation between the SML-portfolio and the EG factor, it does not meet our criteria for statistical significance.

Table 5: The table displays q-factor model regression results. The dependent variable is monthly excess market returns $(R_i - R_f)$. Market coefficient $(R_m - R_f)$, size-factor (ME), investment-to-assets-factor (IA), ROE-factor (ROE), expected-growth-factor (EG), and alpha (α) are reported for each portfolio and the long-short-duration (SML) portfolio. The table also reports number of observations, R-squared. Adjusted R-squared, residual standard error, and F-statistics. We categorize common stocks listed on NYSE, Amex, and Nasdaq into deciles by duration at the end of each June from 1970 to 2022. Portfolio returns and durations are value weighted.

	Dependent variable:										
	Monthly Portfolio Returns 1970-2022										
	Pf1	Pf2	Pf3	Pf4	Pf5	Pf6	Pf7	Pf8	Pf9	Pf10	SML
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
α	0.703^{***}	0.203^{**}	0.071	-0.095	-0.146	-0.129	-0.066	0.058	-0.327^{***}	-0.294^{*}	0.998^{***}
	t = 6.118	t = 1.994	t = 0.804	t = -0.986	t = -1.299	t = -1.185	t = -0.548	t = 0.416	t = -2.675	t = -1.943	t = 5.132
$R_m - R_f$	0.891^{***}	0.987^{***}	1.002^{***}	1.020^{***}	1.078^{***}	1.042^{***}	1.056^{***}	1.037^{***}	1.061^{***}	1.094^{***}	-0.203^{***}
	t = 29.678	t = 35.171	t = 41.204	t = 37.574	t = 34.925	t = 38.444	t = 33.785	t = 37.412	t = 33.053	t = 27.537	t = -3.968
ME	0.102^{**}	0.083^{**}	-0.016	0.041	-0.080^{*}	-0.107^{**}	-0.001	0.002	-0.055	-0.023	0.125
	t = 2.243	t = 2.014	t = -0.403	t = 0.992	t = -1.875	t = -2.529	t = -0.026	t = 0.058	t = -1.117	t = -0.378	t = 1.640
IA	0.146^{**}	0.171^{***}	0.113^{*}	0.093	0.115^{*}	0.100^{*}	0.132^{**}	-0.112	0.031	0.034	0.112
	t = 2.265	t = 2.846	t = 1.660	t = 1.415	t = 1.839	t = 1.700	t = 2.132	t = -1.557	t = 0.606	t = 0.530	t = 1.223
ROE	-0.436^{***}	-0.159^{***}	-0.158^{***}	0.050	0.106^{*}	0.076	0.172^{**}	0.138^{**}	0.209^{***}	0.227^{***}	-0.662^{***}
	t = -7.985	t = -2.838	t = -3.091	t = 0.925	t = 1.676	t = 1.252	t = 2.567	t = 2.339	t = 3.531	t = 3.315	t = -7.167
EG	0.070	0.081	0.182^{***}	-0.008	-0.042	-0.049	-0.069	-0.168^{**}	-0.031	-0.176^{**}	0.247^{**}
	t = 1.030	t = 1.096	t = 3.082	t = -0.114	t = -0.570	t = -0.733	t = -0.972	t = -2.298	t = -0.462	t = -2.485	t = 2.355
Observations	636	636	636	636	636	636	636	636	636	636	636
R^2	0.765	0.794	0.829	0.811	0.795	0.804	0.792	0.806	0.779	0.730	0.171
Adjusted R^2	0.763	0.792	0.828	0.809	0.793	0.803	0.790	0.805	0.777	0.728	0.164
Residual Std. Error (df = 630)	2.478	2.334	2.047	2.262	2.465	2.317	2.456	2.435	2.553	3.090	4.038
F Statistic (df = 5; 630)	409.867^{***}	485.450^{***}	611.625^{***}	539.872^{***}	488.022^{***}	517.608^{***}	478.591^{***}	525.008^{***}	444.434^{***}	340.440^{***}	25.924^{***}
Note:											$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

It may seem counterintuitive that the SML-portfolio, which so far seems to yield exceptional returns, is negatively correlated with the ROE-factor. Looking back at section 3.3.3, we remember that the ROE-factor represents the differential returns between a portfolio of high book equity returns and one comprising of firms with lower returns on book equity.

If ROE is lower than investors' required return on equity, the firm could be inclined to pay out a larger portion of their earnings as dividends rather than reinvesting in future growth. This is perhaps something we could expect from a firm with low implied equity duration.

The regression results exhibit a pattern where portfolios with lower implied equity durations (Pf1 to Pf3) have a negative correlation with the ROE factor. The magnitude of this correlation decreases as duration increases. For the portfolios with mid-range durations (Pf4 to Pf6), the relationship with the ROE factor is not statistically significant at conventional levels, suggesting no clear pattern of correlation based on these results alone.

While portfolios Pf7 and Pf8 show a positive correlation with ROE. However, we do not consider these results statistically significant. They fall short of the strict t-statistic threshold of 3 established for our analysis. Portfolios Pf9 and Pf10, which have higher implied equity duration, do exhibit a statistically significant positive correlation with ROE, aligning with the conjecture thar longer duration forms may be characterized by reinvestment and growth strategies.

The q-factor model has uncovered some intriguing insights. It shows that the SML-portfolio returns have a highly significant negative exposure to low ROE stocks. However, similar to the previous Fama-French models, it falls short of explaining the alpha. We observe a highly significant positive alpha of close to 1%, and the R-squared is still low compared to our other portfolios.

Again, as discussed in section 6.2.2, a monthly alpha of almost 1% may initially be met with skepticism. However, referencing Weber (2018) once more, who reported a highly significant monthly alpha of 1.25 against the Fama-French 5-factor model, adds perspective. Although this is not a like-for-like comparison, it may still suggest that that our findings are relatively conservative.

While it might not necessarily be a negative outcome, one could argue that this gives weight to the idea that the short duration premium could offer returns exceeding the market's pricing of risk factors to which the SML-portfolio is exposed. However, it is important to consider that the SML-portfolio could be subject to systematic risk factors which we have not controlled for. These factors might fully account for the abnormal returns observed thus far. In the next part of our paper, we will analyze our portfolio returns using a factor model which aims to also consider factors related to systematic mispricing.

6.2.4 Stambaugh-Yuan model

We will now move on to analyze our portfolio results using the final factor model in our arsenal, the Stambaugh-Yuan model. This model, detailed in section 3.3.4, combines the traditional market risk-factor and the SMB-factor from the Fama-French models with factors aiming to represent systematic mispricing of stocks. When analyzing the results of the Stambaugh-Yuan model, we will use our heightened t-stat threshold of 3 for our mispricing factors and conventional 5% for our market, size factor and alpha constant. Note that our current sample is limited to monthly portfolio returns between 1970-2016, due to only having access to factor data up until that year.

All portfolios demonstrate statistically significant exposure to the market risk factor. Portfolios Pf2 through Pf10 do not exhibit significant alphas. However, Pf2 and Pf6 show significant positive exposure to the SMB factor, and Pf3 exhibits significant exposure to the MGMT factor.

The model suggests that the SML-portfolio has negative exposure to market risk, positive exposure to the SMB-factor and MGMT-factor, and negative exposure to the PERF-factor, as all coefficients satisfy our t-stat requirements. The economic intuition behind the MGMT and PERF factor is complex (see section 3.3.4). Both mispricing factors are analogous to the SMB-factor and have a similar interpretation. Meaning that like SMB, which is Small-Minus-Big, the mispricing factors have an Underpriced-Minus-Overpriced interpretation. This implies that the SML-portfolio is exposed to firms classified as underpriced due to managerial measures and those classified as overpriced due to performance measures.

Interestingly, the coefficients and significance of these mispricing factors in the SML-portfolio suggest that mispricing anomalies are affecting portfolio returns. The positive coefficient for MGMT and the negative coefficient for PERF imply that the strategy capitalizes on stocks underpriced based on management measures and overpriced based on performance measures. The significant coefficients for these factors indicate that the model is capturing systematic mispricing anomalies, consistent with the Stambaugh-Yuan model’s goal of explaining asset return through such anomalies overlooked by traditional models.

Table 6: The table displays Stambaugh-Yuan model regression results. The dependent variable is monthly excess market returns $(R_i - R_f)$. Market coefficient $(R_m - R_f)$, small-minus-big (SMB), management-factor (MGMT), performance-factor (PERF), and alpha (α) are reported for each portfolio and the long-short-duration (SML) portfolio. The table also reports number of observations, R-squared. Adjusted R-squared, residual standard error, and F-statistics. We categorize common stocks listed on NYSE, Amex, and Nasdaq into deciles by duration at the end of each June from 1970 to 2022. Portfolio returns and durations are value weighted.

	Dependent variable:										
	Monthly Portfolio Returns 1970-2016										
	Pf1	Pf2	Pf3	Pf4	Pf5	Pf6	Pf7	Pf8	Pf9	Pf10	SML
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
α	0.686***	0.267**	0.111	-0.073	-0.095	-0.006	-0.071	0.025	-0.273**	-0.189	0.875***
	t = 5.248	t = 2.409	t = 1.178	t = -0.659	t = -0.773	t = -0.045	t = -0.562	t = 0.174	t = -1.984	t = -1.165	t = 4.145
$R_m - R_f$	0.882***	0.956***	1.017***	1.014***	1.095***	1.024***	1.067***	1.032***	1.057***	1.063***	-0.180***
	t = 21.395	t = 31.343	t = 42.279	t = 33.447	t = 31.042	t = 31.718	t = 29.234	t = 28.163	t = 26.631	t = 22.389	t = -2.794
SMB	0.185***	0.144***	0.016	0.053	-0.092*	-0.136***	-0.002	-0.007	-0.064	-0.034	0.219**
	t = 3.643	t = 3.364	t = 0.391	t = 1.093	t = -1.692	t = -2.665	t = -0.039	t = -0.142	t = -1.079	t = -0.473	t = 2.234
MGMT	0.077	0.116**	0.162***	0.043	0.037	-0.055	0.002	-0.169**	-0.023	-0.186***	0.263***
	t = 1.228	t = 2.107	t = 3.680	t = 0.714	t = 0.561	t = -0.761	t = 0.040	t = -2.545	t = -0.420	t = -2.804	t = 3.064
PERF	-0.148***	-0.047	0.005	0.050	0.058	0.027	0.111**	0.062	0.111***	0.063	-0.211***
	t = -3.720	t = -1.182	t = 0.174	t = 1.308	t = 1.254	t = 0.593	t = 2.575	t = 1.352	t = 2.865	t = 1.430	t = -3.458
Observations	564	564	564	564	564	564	564	564	564	564	564
R^2	0.724	0.783	0.827	0.808	0.792	0.793	0.789	0.802	0.759	0.716	0.105
Adjusted R^2	0.722	0.781	0.826	0.807	0.790	0.792	0.788	0.801	0.757	0.714	0.099
Residual Std. Error (df = 559)	2.642	2.304	2.026	2.220	2.483	2.382	2.468	2.446	2.663	3.200	4.284
F Statistic (df = 4; 559)	366.253***	503.819***	668.064***	589.167***	531.089***	535.920***	523.462***	567.743***	440.661***	352.159***	16.412***
Note:											*p<0.1; **p<0.05; ***p<0.01

Furthermore, the significant alpha in the SML-portfolio suggests that returns are not entirely explained by these four factors. Given that MGMT and PERF are designed to capture mispricing based on management and performance measures, the significant alpha may indicate additional forms of mispricing or anomalies not captured by these two factors. Further investigation into these anomalies could reveal more systematic patterns contributing to portfolio returns.

The model's limited explanation of abnormal returns and low R-squared for the SML-portfolio compared to Pf1 and Pf10, despite the SML's simple long-position in Pf1 and short-position in Pf10, suggest other influencing factors not captured in the model. This could be a unique risk-premium associated with the strategy of going long on short-duration stocks and short on long-duration stocks.

Despite these insights, the consistent generation of abnormal returns in the SML-portfolio in various asset pricing models, remains a mystery. However, the Stambaugh-Yuan model's implication of mispricing in SML returns is intriguing. The Stambaugh-Yuan only considers two mispricing factors. This may suggest that taking a deeper look into mispricing could explain more of the short duration premium than initially thought by the model.

6.3 Mispricing

Based on the intriguing results we got from our Stambaugh-Yuan model, we will in this section delve deeper into the mispricing scores of individual stocks to see if there are some insights that could help explain the short duration premium. Figure 3 displays the mean mispricing scores across ten portfolios categorized by the duration of the stocks they contain, commencing with Pf1 that includes stocks with the shortest duration. And culminating with Pf10, which includes stocks with the longest duration. The visual trend suggests a gradual increase in mean mispricing scores from Pf1 to Pf10, which implies that stocks with a longer duration are potentially prone to mispricing. This observation is consistent with findings from Beckmeyer & Meyerhof (2022).

A possible explanation for the increased mispricing among longer-duration stocks might be the greater uncertainty regarding their cash flows, coupled with their higher sensitivity to fluctuations in discount rates. Furthermore, these stocks might be influenced by investor sentiment, that may lead to an over- or undervaluation. The higher mispricing scores for high duration stocks could also stem from the distinct risk profiles associated with different asset durations; long duration stocks are more susceptible to interest rate changes, which could contribute to more significant mispricing. This is in accordance with the studies mentioned in our literature review in section 2.

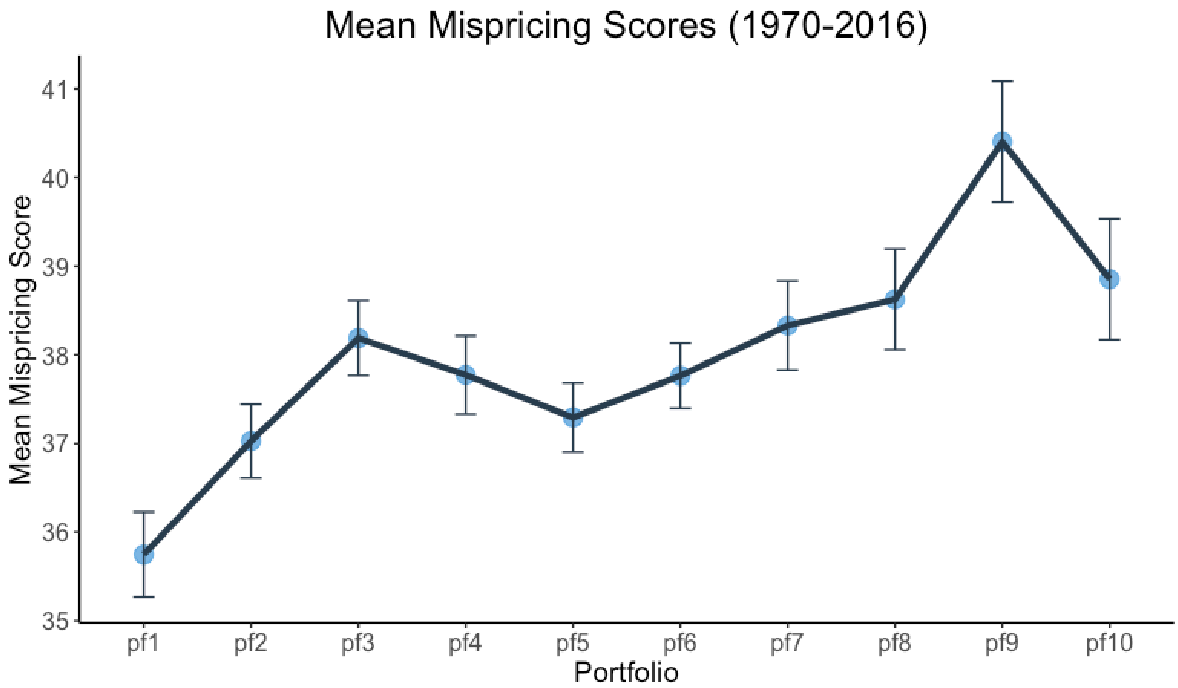
While it may initially appear counterintuitive that long-duration stocks display higher mispricing scores yet yield lower returns compared to their short-duration counterparts, the resolution lies within the mispricing score calculation. This score is the arithmetic mean of a stock's ranking percentiles across 11 mispricing anomalies outlined in section 3.3.4. Higher scores suggest stocks are more 'overpriced', while lower scores indicate 'underpriced' conditions. Consequently, long-duration stocks with their elevated mispricing scores tend to be more overpriced. This could be a consequence of market inefficiencies, such as overly optimistic long-term growth projections, risk underestimation, or heightened investor sentiment.

Conversely, short duration stocks with their lower mispricing scores may indicate that they are closer to their intrinsic value or even underpriced. This may reflect the market's tendency to undervalue their imminent cash flows and/or amplify perceived risks. It could highlight the market's distinct valuation methods, shaped by duration and the perceived risk-reward balance. Therefore, the mispricing measure may illuminate the nuances of market perceptions and speculative behavior, accounting for the overvaluation seen in long-duration stocks and the more grounded valuation approach applied to short-duration stocks.

The graph provides insight into how accurately the market is pricing stocks. It indicates that the market is more efficient in pricing short-duration stocks compared to their long duration counterpart. As evidenced by the lower and more consistent mean mispricing scores within low duration portfolios. Additionally, the graph may offer insights into the existence of a short duration premium. If the mispricing scores for long-duration stocks are elevated due to overvaluation, this could explain the observed trend of lower excess returns for these stocks compared to their short-duration counterparts. Furthermore, the market's risk-reward trade-off could be misaligned. The market may be overestimating the risk of short duration stocks or underestimating risk of long duration stocks. This misalignment might explain the pricing inefficiencies we have observed. These inefficiencies could also explain the short duration premium we have observed, and the positive alpha in our short-minus-long (SML) strategy, detailed in section 6.2

The graph also indicates that even though the mispricing scores are increasing over the increased duration, the mispricing scores' differences between short and long-duration stocks are relatively modest, which might be attributed to the use of value-weighted average scores. The value-weighting gives greater influence to the larger firms within the portfolios. We would assume that larger firms tend to be subject to more rigorous market scrutiny, and consequently, are less susceptible to mispricing. This could potentially explain that we only observe marginal differences in mispricing scores between portfolios.

Figure 3: This figure depicts the average mispricing scores of portfolios 1 though 10 (Pf1-Pf10) between 1970 and 2016. We categorize common stocks listed on NYSE, Amex, and Nasdaq into deciles by duration at the end of each June from 1970 to 2022. Portfolio mispricing scores are for a given year are computed as the sum of value-weighted mispricing score of the stocks in each portfolio.



Lastly, the graph contains confidence intervals given at the 5% level, the intervals are depicted by the whiskers. These intervals illustrate the variance in mean mispricing scores and is highlighted by the differing widths across portfolios. Some portfolios exhibit wider intervals, potentially reflecting stock volatility or liquidity. Notably, the non-overlapping confidence intervals for Pf1 and Pf10 suggest that there is a statistically significant difference in their mean mispricing scores. From the graph, we can see that the higher duration portfolios have a wider confidence interval than their counterparts. The broader intervals, coupled with a higher mispricing score, might imply that long duration portfolios are more vulnerable to market corrections.

7. Conclusion

This master's thesis expands upon existing literature in the field of equity duration by offering a detailed analysis of equity duration and its relationship to portfolio returns. This analysis is significant for understanding stock market dynamics, with a focus on the short duration premium. Building on Weber's (2018) work, we use a comprehensive dataset spanning from 1970 to 2022 and apply various analytical methods to explore the short duration premium.

Our thesis emphasizes portfolio diversification, including data from 894 to 2521 firms annually. This range does not only mitigate idiosyncratic risks but also ensures that our findings reflect wider market trends. A key aspect of our research is the stability of duration estimates. The consistent alignment of average and median implied equity duration over the years highlights their reliability, which have been important in examining the link between equity duration and stock returns. This consistency underpins investment strategies focusing on equity duration and its role in portfolio management.

We discovered a notable short duration premium in the stock market, where stocks with shorter equity durations generally outperformed those with longer durations. This trend was especially pronounced in portfolios of stocks with shorter durations, consistently yielding higher returns than those with longer durations. This pattern is consistent over various market conditions across five decades and suggests a robust and persistent link between shorter equity duration and higher returns, posing a challenge to traditional asset pricing models.

We also analyzed risk-adjusted returns using the Sharpe ratio. Our findings indicate that portfolios with shorter-duration stocks offered higher returns and higher Sharpe ratios compared to longer-duration portfolios. This suggests that the premium for short-duration stocks reflects intrinsic value rather just higher risk compensation. The premium's stability across different market cycles further supports its significance in the equity market.

We employed various factor models to further analyze the short duration premium. Initially, we used the CAPM, which primarily addresses market risk. Although it was somewhat limited in explaining portfolio return variations, it hinted at other influencing factors. The limited explanatory power of the CAPM, along with the significant alpha of the portfolios, led us to explore more complex models, such as the Fama-French three-factor and five-factor models.

These models provided more insights but still didn’t fully account for the returns of the significant alpha produced by the strategy.

We then considered newer asset pricing models such as the q-factor model, which incorporates market risk, size, investment, profitability and expected growth factors. This model gave us some interesting insights regarding the characteristics of the short duration portfolios, it showed significant alpha for our portfolios. Indicating that other factors might influence returns. Our continued exploration led us to the Stambaugh-Yuan model, which includes mispricing factors. This model revealed significant exposure to our portfolios to mispricing factors, indicating systematic market mispricing’s impact on returns. However, a significant alpha remained, highlighting the need to consider market inefficiencies and behavioral aspects in asset pricing.

Shifting our focus from different factor models to mispricing across different equity duration portfolios, we observed an upward trend in mean mispricing scores from short-duration to long-duration stocks. This suggests that longer-duration stocks may be more susceptible to mispricing, potentially contributing to the short duration premium. The diverse mispricing degrees across portfolios, particularly the wider confidence intervals in long-duration portfolios, indicate higher uncertainty or variability in their mispricing.

In conclusion, this thesis provides strong evidence for the existence of a short duration premium and suggest that traditional factor models may not fully capture this phenomenon. This implies the influence of additional factors, possibly related to mispricing and behavioral biases, opening new possibilities for investment strategies focused on short-duration stocks. Additionally, highlighting the need for further research into the unexplained aspects of returns, especially regarding market inefficiencies and behavioral biases.

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9. Appendix

9.1 Appendix 1: Ways of computing equity duration

The calculation of duration for bonds and fixed-income portfolios is made possible by Macaulay's Bond duration formula, which is instrumental in evaluating how sensitive bonds and fixed-income portfolios are to changes in interest rates. This tool has played an important part in the realm of fixed income securities, and there has been interest in developing a comparable metric for equity markets and equity portfolios. Initially, approaches like the dividend discount model were applied to estimate the duration of equities. However, this model often resulted in durations that were excessively long, leading to critiques abouts its representation of equity price elasticity, suggesting it did not accurately reflect market behavior (Lewin & Satchell, 2001).

Leibowitz (1986) presents one of the pioneering studies proposing a method to calculate equity duration. In this study, Leibowitz computes duration by examining the historical correlation between stocks and bonds. The premise is that this correlation, when combined with an established measure of bond duration, can be utilized to extrapolate an estimated duration for the stock market.

Dechow, Sloan & Soliman (2004), and subsequently Weber (2018), introduce a cash-flow based model for estimating equity duration that takes inspiration from Macaulay's formula for bond duration, tailored to address the cash-flow uncertainties inherent in equities and their lack of a fixed maturity date. The model modifies the traditional Macaulay duration framework by dividing it into two segments: an initial finite forecasting period and a concluding infinite horizon, during which cash flows are treated as a constant perpetuity. This bifurcated approach bears resemblance to other equity valuation techniques, such as the dividend discount model.

Schroder & Esterer (2016) is using a more intricate Residual Income Model (RIM) to determine equity duration. This model bears similarities to the cash flow-based approach, but it distinguishes itself by utilizing analyst forecasts for serve as a proxy for a firm's anticipated cash flows. Furthermore, it assumes an increasing trend in terminal cash flows, anchored in long-term macroeconomic indicators, in contrast to the assumption of level-perpetuity employed by the cash-flow model proposed by Dechow et al. (2004).

An alternative approach for modeling equity duration is introduced by Gormsen & Lazarus (2023). Instead of relying on projections of future cash flows, their methodology draws upon variables that are more readily observable and closely related that can be correlated with equity duration. They employ analyst projections of long-term earnings and dividend growth as proxies for duration. Their proposition is rooted in the premise that stocks with high duration are likely to realize a larger portion of their cash-flow in the distant future, whereas the stocks with a low duration are anticipated to realize their cash-flows in the more immediate future. Supporting this notion, Weber (2018) has provided empirical evidence of a strong correlation between calculated equity duration and the projections of long-term growth forecast provided by analysts.

A new and more innovative method of calculating equity duration is provided by van Binsbergen et al. (2013). They utilize dividend futures that extend up to ten years to generate equity yields that is comparable to bond yields. This method integrates elements from both fixed income and equity markets, to facilitate a direct application of Macaulay's bond duration framework to dividend futures. However, there are suggestions that duration they get from this model, that is constrained to a ten-year horizon, may be more consistent with stocks with lower duration due to the characteristics of the cash-flows from the dividend futures.

9.2 Appendix 2: CAPM regression results

Table 7: The table displays CAPM regression results. The dependent variable is monthly excess market returns $(R_i - R_f)$. Market coefficient $(R_m - R_f)$ and alpha (α) are reported for each portfolio and the long-short-duration (SML) portfolio. The table also reports number of observations, R-squared. Adjusted R-squared, residual standard error, and F-statistics. We categorize common stocks listed on NYSE, Amex, and Nasdaq into deciles by duration at the end of each June from 1970 to 2022. Portfolio returns and durations are value weighted.

	Dependent variable:										
	Monthly Excess Portfolio Returns 1970-2022										
	Pf1	Pf2	Pf3	Pf4	Pf5	Pf6	Pf7	Pf8	Pf9	Pf10	SML
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
α	0.596***	0.278***	0.195**	-0.019	-0.073	-0.091	0.042	-0.061	-0.221**	-0.300**	0.896***
	t = 5.379	t = 2.802	t = 2.320	t = -0.213	t = -0.694	t = -0.976	t = 0.418	t = -0.615	t = -2.096	t = -2.345	t = 5.109
$R_m - R_f$	0.926***	0.978***	0.966***	1.007***	1.040***	1.007***	1.026***	1.066***	1.025***	1.088***	-0.162***
	t = 27.689	t = 34.082	t = 43.922	t = 39.445	t = 34.175	t = 36.584	t = 33.089	t = 42.525	t = 34.766	t = 30.081	t = -2.994
Observations	636	636	636	636	636	636	636	636	636	636	636
R^2	0.707	0.781	0.821	0.808	0.788	0.797	0.784	0.801	0.767	0.722	0.029
Adjusted R^2	0.707	0.781	0.821	0.808	0.788	0.797	0.784	0.800	0.767	0.721	0.027
Residual Std. Error (df = 634)	2.754	2.398	2.089	2.268	2.496	2.349	2.490	2.463	2.610	3.124	4.356
F Statistic (df = 1; 634)	1,533.105***	2,259.314***	2,905.385***	2,674.922***	2,356.568***	2,493.787***	2,302.546***	2,544.333***	2,091.335***	1,645.168***	18.793***
Note:											*p<0.1; **p<0.05; ***p<0.01

9.3 Appendix 3: Fama-French 6-factor model + liquidity factor regression results

Table 8: The table displays "Fama-French 6-factor model + liquidity" regression results. The dependent variable is monthly excess market returns $(R_i - R_f)$. Market coefficient $(R_m - R_f)$, small-minus-big (SMB), high-minus-low (HML), robust-minus-weak (RMW), conservative-minus-aggressive (CMA), and alpha (α) are reported for each portfolio and the long-short-duration (SML) portfolio. The table also reports number of observations, R-squared. Adjusted R-squared, residual standard error, and F-statistics. We categorize common stocks listed on NYSE, Amex, and Nasdaq into deciles by duration at the end of each June from 1970 to 2022. Portfolio returns and durations are value weighted.

	Dependent variable:										
	Monthly Excess Portfolio Returns 1970-2022										
	Pf1	Pf2	Pf3	Pf4	Pf5	Pf6	Pf7	Pf8	Pf9	Pf10	SML
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
α	0.518***	0.098	0.119	-0.162*	-0.245**	-0.204**	-0.052	-0.129	-0.349***	-0.395***	0.912***
	t = 4.605	t = 1.014	t = 1.429	t = -1.732	t = -2.320	t = -1.998	t = -0.515	t = -1.235	t = -3.096	t = -2.768	t = 4.896
$R_m - R_f$	0.919***	0.998***	0.997***	1.027***	1.077***	1.048***	1.063***	1.062***	1.064***	1.108***	-0.190***
	t = 29.113	t = 37.088	t = 40.116	t = 40.127	t = 37.035	t = 38.997	t = 35.588	t = 41.963	t = 34.795	t = 29.435	t = -3.728
SMB	0.185***	0.144***	0.017	0.082**	-0.026	-0.053	0.037	0.072*	-0.043	0.048	0.137*
	t = 4.226	t = 3.868	t = 0.449	t = 2.020	t = -0.648	t = -1.243	t = 0.755	t = 1.770	t = -0.872	t = 0.882	t = 1.810
HML	0.200***	0.173***	0.071*	-0.005	0.012	-0.083*	-0.181***	-0.213***	-0.165***	-0.265***	0.465***
	t = 3.504	t = 3.442	t = 1.671	t = -0.105	t = 0.232	t = -1.668	t = -3.470	t = -4.453	t = -3.051	t = -3.955	t = 5.641
RMW	-0.126**	0.122**	0.086*	0.169***	0.228***	0.199***	0.248***	0.213***	0.233***	0.242***	-0.367***
	t = -2.325	t = 2.155	t = 1.710	t = 3.059	t = 3.635	t = 3.490	t = 3.899	t = 3.841	t = 3.990	t = 3.435	t = -4.110
CMA	0.063	0.063	0.091	0.134*	0.074	0.164**	0.278***	0.131	0.210***	0.272***	-0.209*
	t = 0.693	t = 0.793	t = 1.182	t = 1.846	t = 1.092	t = 2.306	t = 3.479	t = 1.640	t = 2.630	t = 3.083	t = -1.650
MOM	-0.034	-0.002	-0.029	-0.008	0.037	-0.007	-0.039	-0.004	0.028	-0.005	-0.028
	t = -1.432	t = -0.078	t = -1.644	t = -0.342	t = 1.615	t = -0.291	t = -1.348	t = -0.206	t = 1.145	t = -0.188	t = -0.717
LIQ	0.095***	0.106***	-0.010	0.089***	0.089**	0.040	-0.051	0.067**	0.002	-0.006	0.101**
	t = 2.604	t = 3.246	t = -0.349	t = 2.947	t = 2.343	t = 1.273	t = -1.587	t = 2.152	t = 0.070	t = -0.165	t = 2.087
Observations	636	636	636	636	636	636	636	636	636	636	636
R^2	0.749	0.808	0.828	0.819	0.802	0.808	0.800	0.815	0.782	0.736	0.151
Adjusted R^2	0.746	0.806	0.826	0.817	0.800	0.806	0.798	0.813	0.779	0.733	0.142
Residual Std. Error (df = 628)	2.563	2.256	2.055	2.216	2.423	2.294	2.409	2.382	2.540	3.056	4.091
F Statistic (df = 7; 628)	267.878***	377.552***	432.782***	405.635***	363.662***	378.743***	358.682***	395.644***	321.621***	250.656***	16.003***
Note:											*p<0.1; **p<0.05; ***p<0.01