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Volatility Managed Short Duration Premium

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Abstract

This thesis investigates if the short duration premium of the equity duration strategy can be improved by managing its volatility. Based on estimates by Gonçalves (2021), we replicate equity duration sorted portfolios of U.S. stocks from 1973 to 2019, and identify a 9.3% premium for a strategy buying short duration firms, and selling long duration firms. These findings support literature suggesting the existence of a downward-sloping equity term structure. Managing the volatility of the equity duration strategy results in a reduction of 4.2% annualized risk-adjusted return, suggesting that volatility management does not lead to an improvement of the short duration premium. In contrast to strategies for which volatility management increases premiums, we note that the original equity duration strategy has a high positive skewness of 0.64, which is completely diminished. We argue that volatility management is not suitable for the equity duration strategy as strategy returns are generally high in periods of high volatility, and returns are generally low in periods of low volatility. We finalize our exploration of the short duration premium by testing its merits in a multi-factor environment. We show that combining the equity duration strategy with traditional asset pricing models in Markowitz's (1952) portfolio optimization model increases Sharpe ratios significantly. Our findings underscore the viability of the equity duration investment strategy but warn investors of scaling investments to its volatility.

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1 Introduction

Recent studies suggest a downward-sloping equity term premium, indicative of a lucrative investment opportunity for sophisticated investors: *Implied Equity Duration: A New Measure of Equity Risk* (Dechow, Sloan, & Soliman, 2004), *Cash flow duration and the term structure of equity returns* (Weber, 2018), *The short duration premium* (Gonçalves, 2021), and *Time variation of the equity term structure* (Gormsen, 2021). The net-zero equity duration strategy of the short duration premium is harvested by buying assets with expected cash flows concentrated in the short-term, while selling those with expected cash flows concentrated in the long-term. The strategy has proven to yield high, positive risk-adjusted returns (Gonçalves, The short duration premium, 2021). The merits of the equity duration strategy in combination with traditional asset pricing models is yet to be explored.

The investment strategy of volatility management increases portfolio exposure in periods of low volatility and decreases portfolio exposure in periods of high volatility (Barroso & Santa-Clara, 2015) (Moreira & Muir, 2017). Volatility management has proven to yield improved risk-adjusted returns, alphas and utility gains for mean-variance investors for many, but not all, well-established factor strategies.

In this thesis, we contribute to the existing literature by exploring the short duration premium in combination with volatility management, and in combination with well-established investment strategies. To determine whether managing the volatility of the short duration premium yields higher risk-adjusted returns, we construct portfolios based on Gonçalves' (2021) yearly equity duration estimates for U.S. stocks from 1973 until 2019, and follow Moreira and Muir's (2017) variance prediction to determine strategy exposure. Our study contributes further by exploring the role of the short duration premium in a multifactor environment of traditional asset pricing models, building on the portfolio optimization model by Markowitz (1952). The relative increase in the optimized portfolio's Sharpe ratio indicates whether the consideration of equity duration shows merit to sophisticated investors.

In *2.1 Replication of the Equity Duration Strategy,* we confirm that the creation of value- and equal weighted duration sorted portfolios is done according to Gonçalves' (2021) method by comparing average firm characteristics for each decile portfolio. We establish the existence of a short duration premium of 9.3% and 8.8% for value- and equal weighted portfolios, respectively, in which there are insignificant differences to those of Gonçalves. We further confirm that equity duration does in fact drive this premium by presenting positive and highly significant strategy alphas of 11%, 8%, and 6% in regressions on CAPM, the Fama-French three- and five plus momentum factor models, respectively. These results legitimize our method for establishing the short duration premium used for volatility management and the multifactor model.

In *2.2 Volatility Managed Short Duration Premium,* we find that applying volatility management to the equity duration strategy does not yield improved risk-adjusted returns. Interestingly, excess returns decrease by 4.2% and 1.6% for value- and equal weighted portfolios, respectively. The detriment of returns is explained in an analysis of the positive relationship between the short duration premium and portfolio variance. Furthermore, we find that volatility managing the equity duration strategy reduces the skew in returns from 0.64 to -0.01. The elimination of positive skewness is a distinct contrast to the successful volatility management of traditional asset pricing models presented in previous studies (Moreira & Muir, 2017), in which the negative skewness of strategy returns is corrected. We hypothesize that the poor effect of volatility management may be due to either 1) an inaccurate prediction of variance, or 2) cyclicality effects of the short duration premium. First, we verify that Moreira and Muir’s (2017) measure is sufficiently accurate in predicting realized variance by comparing its effectiveness to that of Barroso and Santa-Clara’s (2015) variance prediction. Second, we find a mismatch between the characteristics of the equity duration strategy and volatility management, as negative returns are emphasized due to the correlation between volatility and returns. Interestingly, the characteristics of the short duration premium coincide with those of other factor strategies for which volatility management does not yield improved risk-adjusted returns. To conclude the chapter, we adjust our short duration portfolio to reduce noise and potential transaction costs. We find that the short duration premium and the results from its volatility management remain fairly unchanged.

In *2.3 Optimizing the Multifactor Model,* we document increased Sharpe ratios when combining the equity duration strategy with traditional asset pricing models based on Markowitz’ (1952) portfolio optimization model. We find an increase in Sharpe ratios of 0.21, 0.14, and 0.12 when combining the short duration portfolio with Fama-French's three-, five- and five plus momentum factor models, respectively. The increases in risk-adjusted returns suggest that the consideration of assets' equity duration is a valid aspiration for sophisticated investors.

The contributions of our analyses compliment that of existing research on the short duration premium. The downward-sloping equity term structure has been empirically identified though several approaches. Dechow et al. (2004) identify an annualized short duration premium of 24.1% between firms with duration estimates of less than one year and more than 20 years. They present an equity duration measure of forecasted cash flows based on firms' accounting data but show that the book-to-market ratio can be used as a crude measure of duration. Binsbergen et al. (2012), demonstrate the short duration premium between the yield of dividend strips of up to three years and the S&P500 index, with a 9% annual CAPM alpha. Using Dechow et al.'s (2004) duration measure, Weber (2018) creates duration sorted decile portfolios and finds a 15.5% short duration premium. To better align assumptions of the equity duration measure with empirical findings, Gonçalves (2021) adjust the firm-level duration approach of Dechow et al. (2004). Gonçalves (2021) identifies a premium of 8.6% between short- and long duration decile portfolios. His duration measure differs from that of Dechow et al. mainly in its assumption of level cash flows in perpetuity and the recognition of correlations between state variables included in the measure. Gonçalves finds that the premium is long-lived as it persists for at least five years, and is substantial even for large firms in the highest NYSE quartile. This thesis builds on Gonçalves' approach to identify the short duration premium and contributes to the existing creation of duration portfolios by suggesting adjustments of reduced random noise and implied transaction costs.

Beyond identifying the short duration premium, the exploration of the strategy's characteristics is lacking. The most prominent contribution is Gormsen's (2021) assessment of the cyclicality of the premium. Studying the difference between the yield of short dividend strips and the market index, Gormsen shows that the short duration premium is countercyclical, yielding a negative premium in periods of high dividend-price ratios. We compliment Gormsen's findings by confirming the countercyclicality of the premium, but with Gonçalves' (2021) duration measure and altered definitions of bad and good economic times.

We contribute further to the exploration of the short duration premium's characteristics by shedding light on the positive relationship between volatility and return in our analysis of the functionality of volatility managing the strategy.

Volatility is at the center of asset management decisions and has been extensively researched (Andersen et al., 2001). Theories most closely related to this thesis consider "realized" volatility, a term coined by Andersen et al. (2001), exploiting volatility information in high frequency, intradaily changes in returns to make investment decisions. Realized volatility has proven to be a more effective modelling tool than historical returns for predicting future returns (Andersen et al., 2001). Scaling strategy exposure relative to realized volatility to improve risk-adjusted returns, has since been applied to various assets and portfolios. Fleming et al. (2001, 2003) find substantial gains in switching from daily to intradaily returns when varying the exposure of assets for individual stocks, bonds, and gold. Barroso and Santa-Clara (2015) manage the volatility of the momentum strategy, which nearly eliminates strategy crashes and almost doubles the Sharpe ratio. Contrastingly to the short duration premium, momentum is characterized by great negative skewness and high kurtosis (Barroso & Santa-Clara, 2015) – a distinction we highlight in our analysis of the volatility managed short duration premium. Inspired by the success of the volatility managed momentum strategy, Moreira and Muir (2017) apply volatility management to various aggregate factor strategies. Managing the volatility of the market portfolio (MKT), the high-minus-low- (HML), the robust-minus-weak (RMW) and the momentum- (MOM) strategy has proven to yield increased risk-adjusted returns, alphas, and utility gains for mean-variance investors. However, they find that volatility managing the small-minus-big (SMB) and the conservative-minus-aggressive (CMA) strategy does not improve risk-adjusted returns. We contribute to the research of volatility management by exploring its merits for yet another investment strategy, the equity duration strategy, and find that it does not improve risk-adjusted returns. Additionally, by comparing the various volatility managed investment strategies, we provide insights into which strategy characteristics appear central to the success of volatility management.

Our final contribution is to include the equity duration strategy in an optimized multifactor portfolio. Markowitz's (1952) paper, *Portfolio Selection*, presents a model that optimizes the weights of risky assets to maximize an investors' Sharpe ratio through diversification. Moreira and Muir (2017) present an adjusted portfolio model that optimizes the combination of factor strategies instead of individual assets. We contribute to the multifactor model by including the short duration premium, further increasing the Sharpe ratio of the optimized portfolio.

The analysis of this thesis consists of three main chapters. In *2.1* Replication of the Equity Duration Strategy, we replicate the equity duration portfolios of Gonçalves (2021) to confirm the short duration premium in our data sample. In *2.2* Volatility Managed Short Duration Premium, we explore the effect of combining the short duration premium with volatility management. Finally, in *2.3* Optimizing the Multifactor Model, we seek to maximize investors' Sharpe ratios by combining the equity duration strategy with other traditional asset pricing models.

2 Analysis

2.1 Replication of the Equity Duration Strategy

This chapter provides a comprehensive description of our replication of Gonçalves' (2021) equity duration portfolios. First, we account for the data sources that have been used to gather the necessary information, and the restrictions we apply to our data sample. Second, we give a detailed account of the creation of equity duration portfolios. Third, we provide a comparative analysis of our portfolios, to that of Gonçalves (2021).

2.1.1 Data Sources and Restrictions

2.1.1.1 Data and Sources

To create the equity duration portfolios, we use Gonçalves' (2021) yearly duration estimates, and publicly available monthly stock return data, yearly accounting data, and monthly factor return data for traditional asset pricing models.

This paper utilizes the publicly available firm-level duration file, downloaded from Gonçalves' (2021, 3) website. The file contains yearly duration values for firms listed on NYSE, AMEX, and NASDAQ, from 1973 to 2019. Gonçalves' duration measure, *Dur,* is calculated based on twelve state variables, split into four firm characteristic categories of valuation-, growth-, profitability-, and capital structure measures[1]. Annual accounting data and stock return data is required to create yearly equity duration measures for each firm.

As we use Gonçalves' (2021, 3) pre-calculated duration estimates, accounting data is only utilized for descriptive statistics when comparing our portfolio formation with that of Gonçalves (2021). We download accounting data for all firms listed on NYSE, AMEX, and NASDAQ from June 1973 until June 2019 from the Compustat website (Compustat Daily Updates - Fundamentals Annual). To combine Compustat accounting data with CRSP stock return data, we use Wharton's CRSP/Compustat Merged (CCM) database to merge across the firm identifiers in CRPS (PERMNO) and Compustat (GVKEY) (WRDS Overview of CRSP/COMPUSTAT Merged (CCM)).

Monthly and daily stock return data from June 1973 until June 2019 is retrieved from the Center of Research in Security Prices (CRSP Monthly Stock) (CRSP Daily Stock). Monthly stock returns are used for portfolio replication, while daily stock returns are used for volatility management. Stock return data covers U.S. stocks and includes firms listed on NYSE, AMEX, and NASDAQ exclusively. To replicate Gonçalves' (2021) portfolios, we download stock returns, share prices, shares outstanding, delisting return, and delisting code.

We download three datasets from Kenneth French's Data Library: monthly return of the Fama French five factors (Description of Fama/French 5 Factors (2x3)), monthly return of the momentum factor (Detail for Monthly Momentum Factor (Mom)) and market equity breakpoints based on NYSE stocks (Detail for ME Breakpoints). The five Fama-French factors include the market minus risk-free rate (MKT), size (SMB), value (HML), profitability (RMW), and investment (CMA). The monthly US T-bill is used as the risk-free rate. Portfolios are value weighted returns of all stocks listed in the U.S. on NYSE, AMEX, or NASDAQ with a share code equal to ten or eleven. For more technical information on data requirements, we refer to Kenneth French's Data Library.

2.1.1.2 Data Cleaning

The CRSP monthly stock file requires modifications to align with Gonçalves' (2021) portfolios.

[1] See Appendix 1 for details on Gonçalves' (2021) approach to calculating the equity duration estimate.

When a delisting code is available, we use the delisting return from CRSP. However, when a delisting return is not provided, we utilize a return of -30% for delistings classified as Liquidations or Dropped listings (400≤ dlstcd ≤599), and 0% otherwise (Shumway, 1997). When there is no delisting code and no delisting return available for the last observation of any company, we assume a delisting return of -30% for the firm's final observation. Occasional missing return values, not caused by a delisting, are ignored. As a consequence, portfolio returns are likely to be understated relative to the truth, as the weight assigned to one firm is occasionally multiplied with a missing return value[2].

On a note of precaution, in the dataset of 1,3 million observations downloaded from CRSP with a coinciding duration estimate from Gonçalves (2021, 3), we are missing 28 observations of monthly stock data that Gonçalves (2021) includes in his analysis. These are observations where Gonçalves provides an equity duration estimate, and where we do not have stock data available. As Gonçalves (2021) does not elaborate on the use of any additional data sources, we remove these 28 observations. We are comfortable ignoring this misalignment in our dataset, as the low number of missing observations will not have a significant effect on returns.

2.1.1.3 Restrictions

As a result of using equity duration estimates provided by Gonçalves (2021), we apply the same restrictions to our dataset. The firms in our analysis are therefore restricted to:

1. Common stocks of firms incorporated in the U.S. (shred = 10 or 11)
2. Trading on NYSE, AMEX, or NASDAQ (exchcd = 1,2 or 3)
3. Excluding utilities ($4900 \leq SIC \leq 4949$)
4. Excluding financials ($6000 \leq SIC \leq 6999$)
5. Minimum two previous years of data in Compustat, to avoid backfilling concerns

Further restrictions specific to value weighted and equal weighted portfolios are presented in *2.1.2.1 Value Weighted Portfolios* and *2.1.2.2 Equal Weighted Portfolios*, respectively.

[2] Understated portfolio returns only apply to value weighted portfolios, described in 3.3 Portfolio Formation, as firm weights are redistributed yearly.

Table 1:
Duration Distribution for the Sample of Firms

The table provides an overview of the distribution of firms' duration estimates across time, that are included in our data sample. In the first column, a "Year" is defined as starting in July of year t until June of year t+1, following Gonçalves (2021)*. The second column shows the number of firms included in our analysis per year. The duration deciles columns present the maximum duration value within the first, fifth and ninth duration decile. We use Gonçalves' (2021, 3) duration estimates. Firm distribution is presented every fifth year, from 1973 until 2017. We do not include 2018 to align our results with those of Gonçalves. Gonçalves' results are shown in parentheses to the right of our results for comparison purposes.*

Year	Number of Firms	1st Duration Decile	5th Duration Decile	9th Duration Decile
1973	1507 (1507)	5 (5)	20 (20)	55 (55)
1978	2538 (2540)	6 (6)	16 (16)	37 (37)
1983	2455 (2455)	10 (10)	30 (30)	67 (67)
1988	2689 (2690)	14 (15)	37 (37)	88 (88)
1993	2858 (2860)	19 (19)	46 (46)	104 (104)
1998	3304 (3308)	27 (27)	57 (57)	135 (135)
2003	2827 (2831)	15 (15)	43 (43)	101 (101)
2008	2399 (2402)	25 (25)	50 (50)	112 (112)
2013	2125 (2126)	20 (20)	42 (43)	103 (103)
2017	1920 (1922)	25 (25)	51 (51)	136 (136)
Average	2551 (2554)	17 (17)	39 (39)	95 (95)

Table 1 provides an overview of the number of firms and distribution of firms' equity durations for select years, for our and Gonçalves' data sample. We see that our data sample is almost an exact replica of Gonçalves' (2021). This is not surprising as we restrict our monthly CRSP dataset of returns to only include those that we are able to match with a firm and time-specific duration estimation provided by Gonçalves. The maximum deviation in the number of firms per year is four and is due to 28 missing observations in the CRSP dataset, as discussed in section *2.1.1.2 Data Cleaning*.

2.1.2 Portfolio Formation

We follow Gonçalves' (2021) method closely when creating value weighted and equal weighted portfolios to ensure the accuracy of our portfolio replication results. The replication of portfolios is based on our interpretation of Gonçalves' approach as presented in his paper *The short duration premium* (2021).

2.1.2.1 Value Weighted Portfolios

To construct value weighted duration sorted portfolios, we define ten duration thresholds based on firms in our sample listed on NYSE, and thereafter allocate all remaining firms from NASDAQ and AMEX into the ten duration portfolios. The use of NYSE breakpoints, as first implemented by Fama and French (1993), ensures that no portfolio consists only of stocks listed on either NASDAQ, NYSE, or AMEX stock exchanges. As firms listed on NASDAQ and AMEX are traditionally smaller in market equity than those listed on NYSE, the twelve firm-specific variables Gonçalves (2021) bases his duration measure on, might cause a bias by naturally assigning firms from the same stock exchange into the same few portfolios. As a result of applying NYSE breakpoints, there will be a different number of firms in each one of our value weighted decile portfolios.

For value weighted portfolios, firm weights are determined by firms' market equity at the end of June of year *t-1*. Following Gonçalves (2021), firm weights remain constant from June of year *t-1* until the next portfolio is constructed, 12 months later. In reality, maintaining constant stock weights throughout the year means continuously buying and selling stocks to outbalance stock price fluctuations until the next reweighing of stocks. Firm delisting is identified in three ways: by 1) an applicable delisting return, 2) an applicable delisting code, or 3) if there is no return data for a firm in the next 12 months. The sum of the weights of all firms that are delisted in month *m* is redistributed to the weights of all remaining firms in month *m+1*. This ensures that the sum of portfolio weights equal to 1 in each month until the next portfolio creation, 12 months later.

2.1.2.2 Equal Weighted Portfolios

To construct equal weighted portfolios, we completely exclude microcaps so that average returns are not unduly based on small firms. Following Hou, Xue, and Zhang (2015), we exclude all firms in year *t,* starting in July*,* if they have market equities below the 20% quantile in June of year *t-1*, based on NYSE breakpoints retrieved from Kenneth French's Data Library (Detail for ME Breakpoints). For each year, all remaining firms in our sample are then sorted on duration and allocated to decile portfolios. There is an equal number of firms in each equal weighted portfolio as of July of each year. Following Gonçalves' (2021) methodology, equal weighted portfolios are rebalanced monthly to a weight of $\frac{1}{N}$. The delisting of firms is automatically accounted for as there is monthly re-weighing of firms on monthly stock return data for equal weighted portfolios.

2.1.3 Replication Results

To confirm the validity of the short duration premium portfolio used as the basis for volatility management and the multifactor model, we compare our equity duration portfolios with those of Gonçalves (2021). We define the decile with the lowest duration as the *Short duration portfolio*, and the decile with the highest duration as the *Long duration portfolio*. The short duration premium is a net-zero strategy attained by buying the Short duration portfolio and selling the Long duration portfolio. The investment strategy of the Short- minus Long duration portfolio is referred to as *SML* hereafter.

Table 2 reports the performance of each value- and equal weighted decile, for ours and Gonçalves' (2021) portfolios[3]. For both value weighted and equal weighted portfolios, the results indicate a performance of about 13% annualized returns for the Short duration portfolios. When moving towards the Long duration portfolio there is a steady decrease in performance, as shown by decreasing returns[4] and Sharpe ratios. In line with Gonçalves' results, the Long duration portfolios show a mere 4% annualized return. The short duration premium is 9.3% for value weighted portfolios and 8.8% for equal weighted portfolios, as opposed to 8.6%[5] and 9.3%[6] in Gonçalves (2021), respectively. The short duration premiums are significantly different from zero at a 5% significance level for both value weighted and equal weighted portfolios. The differences in the short duration premiums may be explained by deviations in the treatment of missing returns in the CRSP dataset and possible deviations

[3]To ensure the accuracy of the replication of Gonçalves' equity duration strategy, we provide a comparison of ours and Gonçalves' results for a comprehensive set of characteristics in Appendix 3. The firms' characteristics within each of our duration portfolios are similar to the findings of Gonçalves (2021). The slight deviations are attributable to minor differences in the allocation of firms to portfolios or in data cleaning methodology.
[4] See Appendix 4 for a visual presentation of the downward-sloping equity term premium.
[5] The value weighted portfolios consist of an average of 2 firms too many, as compared to those of Gonçalves. There is no clear trend in the deviation of firms. Differences might be due to treatment of abnormalities in the return and delisting return variables from CRSP.
[6] The equal weighted portfolios consist of an average of 16 firms too few, as compared to those of Gonçalves. There is a clear increasing trend in the deviation of firms across time. The deviation might be due to different approaches to the exclusion of microcaps. This paper excludes microcaps based on public NYSE breakpoints (Detail for ME Breakpoints), while Gonçalves (2021) does not detail his approach for the exclusion of microcaps.

Table 2:
Performance of Duration Portfolios

The table presents the performance of our value- and equal weighted portfolios (left), as well as Gonçalves' (2021) *portfolios performance (right). Our sample runs from July 1973 to June 2019. We use Gonçalves' (2021, 3) duration estimates. Value weighted portfolios are created based on NYSE sample breakpoints every June (1973 to 2018) and equal weighted portfolios are created monthly. Microcaps, defined as firms with market equities below the 20% NYSE breakpoints, are excluded from equal weighted portfolios. The table shows annualized average monthly returns (x 12) and Sharpe ratios (x $\sqrt{12}$). t_{stat} is reported in parentheses and tests if there is a difference in return between portfolio Short and Long.*

Panel A: Value Weighted Portfolio Performance					
Duration	Our results		Duration	Gonçalves (2021)	
decile	Excess return	Sharpe ratio	decile	Excess return	Sharpe ratio
Short	13.0 %	0.66	Short	12.7 %	0.66
2	11.7 %	0.66	2	11.5 %	0.66
3	12.7 %	0.72	3	12.5 %	0.72
4	12.0 %	0.72	4	11.6 %	0.71
5	11.1 %	0.66	5	11.0 %	0.67
6	9.1 %	0.57	6	8.8 %	0.55
7	8.5 %	0.52	7	8.1 %	0.50
8	7.5 %	0.42	8	7.3 %	0.42
9	5.6 %	0.29	9	5.5 %	0.30
Long	3.7 %	0.17	Long	4.1 %	0.20
SML	9.3 %	0.59	SML	8.6 %	0.57
(t_{SML})	*(6.25)*		*(t_{SML})*	*(3.55)*	

Panel B: Equal Weighted Portfolio Performance					
Duration	Our results		Duration	Gonçalves (2021)	
decile	Excess return	Sharpe ratio	decile	Excess return	Sharpe ratio
Short	12.6 %	0.63	Short	12.9 %	0.64
2	13.3 %	0.70	2	14.2 %	0.73
3	12.9 %	0.68	3	12.9 %	0.68
4	11.9 %	0.63	4	12.4 %	0.65
5	11.4 %	0.61	5	11.2 %	0.59
6	10.9 %	0.57	6	11.2 %	0.57
7	10.0 %	0.50	7	9.7 %	0.49
8	8.6 %	0.42	8	8.8 %	0.43
9	6.8 %	0.31	9	6.5 %	0.29
Long	3.8 %	0.15	Long	3.6 %	0.13
SML	8.8 %	0.61	SML	9.3 %	0.61
(t_{SML})	*(4.15)*		*(t_{SML})*	*(3.32)*	

in the allocation of firms to duration portfolios. However, the premiums we identify in our data sample, and those of Gonçalves, do not differ at the 10% level of significance.

Table 3:
Factor Regressions of SML

The table displays the regression results of the short duration premium for value weighted duration portfolios, regressed on CAPM, Fama-French three- and five factor plus momentum. Our sample runs from July 1973 to June 2019. Value weighted duration portfolios are created every June (1973 to 2018) based on duration estimates from Gonçalves (2021, 3). We include monthly returns of explanatory variables: the market (MktRF), size (SMB), book-to-market (HML), profitability (RMW), investments (CMA), and momentum (MOM). The first five factors are factors from Fama-French (1996, 2015) and momentum is from Jegadeesh & Titman (1993). *Excess market return (MktRF) is the market return minus the U.S. monthly T-bill rate. Returns are first annualized before time-averaged within each portfolio. Numbers in bold illustrates statistically significant coefficients at the 5% level.* t_{stat} *is reported in parentheses.*

Duration	CAPM		Fama and French 3-factors			
decile	αCAPM	βMKT	αFF3	βMKT	βSMB	βHML
Short	**0.06**	**0.98**	0.03	**0.98**	**0.57**	**0.48**
2	**0.05**	**0.97**	**0.03**	**0.96**	**0.38**	**0.31**
3	**0.06**	**0.98**	**0.04**	**0.99**	**0.26**	**0.29**
4	**0.05**	**0.95**	**0.04**	**0.98**	**0.07**	**0.24**
5	**0.04**	**0.98**	**0.04**	**0.98**	0.04	**0.08**
6	**0.03**	**0.92**	**0.02**	**0.93**	-0.02	0.08
7	0.02	**0.96**	0.02	**0.97**	**-0.06**	-0.02
8	0.00	**1.05**	0.00	**1.04**	-0.03	**-0.10**
9	**-0.03**	**1.14**	**-0.02**	**1.13**	0.00	-0.06
Long	**-0.05**	**1.26**	**-0.05**	**1.22**	**0.08**	**-0.14**
SML	**11.0%**	**-0.28**	**8.0%**	**-0.24**	**0.49**	**0.62**
(t_{SML})	*(5.02)*	*(-6.69)*	*(3.83)*	*(-6.51)*	*(8.97)*	*(10.89)*

Duration	Fama and French 5-factors and Momentum						
decile	αFF5	βMKT	βSMB	βHML	βRMW	βCMA	βMOM
Short	0.03	**0.98**	**0.62**	**0.35**	**0.19**	0.16	**-0.14**
2	0.02	**0.97**	**0.44**	**0.24**	**0.23**	0.06	**-0.08**
3	**0.03**	**1.00**	**0.35**	**0.18**	**0.34**	0.11	**-0.11**
4	**0.04**	**0.98**	**0.12**	**0.18**	**0.17**	0.06	**-0.06**
5	**0.02**	**1.02**	**0.06**	0.04	**0.1**	**0.13**	**0.05**
6	0.01	**0.97**	0.04	0.01	**0.25**	**0.15**	0.02
7	0.02	**0.97**	-0.01	**-0.13**	**0.19**	**0.14**	**-0.1**
8	0.01	**1.03**	-0.03	**-0.19**	0.00	**0.12**	**-0.11**
9	-0.01	**1.10**	0.05	**-0.21**	**0.18**	0.11	**-0.25**
Long	**-0.03**	**1.18**	**0.08**	**-0.19**	0.01	-0.03	**-0.19**
SML	**6.0%**	**-0.20**	**0.54**	**0.54**	**0.18**	0.19	0.05
(t_{SML})	*(2.82)*	*(-5.01)*	*(9.19)*	*(6.82)*	*(2.38)*	*(1.61)*	*(1.12)*

Now that the existence of the short duration premium is established, we wish to verify that the premium still holds when including other explanatory variables. *Table 3* reports results from regressing the returns of each of the equity duration portfolios on traditional asset pricing models.

Table 3 shows beta coefficients for the CAPM-, Fama-French three- and five factor model regressions for each decile portfolio and the SML net-zero strategy. The CAPM regression results show that market betas increase steadily to >1 as we go from the Short duration portfolio to the Long duration portfolio. The annualized and highly significant CAPM alpha of 11%[7] for SML is therefore even larger than the raw short duration premium of 9.3%. As suspected from a relatively low Long duration portfolio returns of 4%, the alpha of the Long duration portfolio is negative, as firms perform worse than the market.

Regressing the portfolio on additional risk factors from the Fama-French three factor model, we maintain a positive and statistically significant alpha for the equity duration strategy[8]. The factors SMB and HML partially explain the short duration premium, as our alpha decreases from 11% to 8%. As the coefficients of SMB and HML are both positive, we argue that the SML strategy bets on small firms and high book-to-market firms. These results align with portfolio trends for size and value variables found in *Appendix 3: Firm Characteristics in Duration Portfolios*. All factors are statistically different from zero in the regression of the short duration premium.

In the Fama-French five factor model plus momentum, we maintain a strong positive alpha for the short duration premium. The alpha falls slightly from 8% to 6%, and the explanatory power of the market and the HML factor decrease somewhat when including RMW, CMA and MOM. A significant positive RMW coefficient indicates that the SML strategy bets on firms with robust operating profitability[9].

Based on the similarity in returns and characteristics of ours and Gonçalves' (2021) equity duration portfolios, we conclude that our portfolios are adequately similar to those of Gonçalves. The short duration premium of the Short- minus Long duration portfolios are used for further analysis in 2.2 Volatility Managed Short Duration Premium and 2.3 Optimizing the Multifactor Model.

[7] Gonçalves (2021) finds alpha of 10% in regressions of the short duration premium on CAPM.
[8] Gonçalves (2021) does not provide results from a Fama-French three factor model regression.
[9] Gonçalves (2021) does not provide results from a Fama and French 5-factor plus momentum model but reports a 4.6% alpha for the Fama-French 5-factor model. We choose to add momentum to our regressions to maintain consistency with the volatility management chapter of this paper - momentum being a vital factor for volatility management analysis.

2.2 Volatility Managed Short Duration Premium

In the previous section, we identify the substantial short duration premium of the SML strategy, in line with the findings of Gonçalves (2021). We will now explore whether the short duration premium may be further optimized in the combination with volatility management. First, we present the concept of volatility managed portfolios. Second, we introduce the SML variable to a volatility management approach. Third, we present the results of a volatility managed SML strategy (hereby SML*). Fourth, we investigate the predictability of the variance measurement used in our volatility managed strategy. Fifth, we analyze the volatility managed SML strategy's performance exclusively in good and bad times. Finally, we confirm our volatility management results by introducing an alternative SML portfolio, with increased robustness to noise and transaction costs.

2.2.1 Volatility Managed Investment Strategies

The approaches of volatility management that are the closest aligned with this thesis, are those of Barroso and Santa-Clara (2015), and Moreira and Muir (2017). Volatility management is based on two concepts: first, that volatility is very predictable, and second, that returns are very hard to predict (Moreira & Muir, 2017). This method takes less risk in periods with high volatility, and higher risk in periods with low volatility, which has proven to increase the gain for mean-variance investors. As volatility is generally high during market crashes, volatility management is designed to limit the exposure to the most negative returns. Therefore, creating a strategy that levers up - increasing exposure to the strategy when volatility is low and reducing exposure when volatility is high - could outperform the original buy-and-sell advice.

Barroso and Santa-Clara (2015) focus on the volatility management of the momentum strategy and find that the strategy nearly eliminates crashes and almost doubles the Sharpe ratio. The original momentum strategy has had remarkable performance over the Fama-French factors but has also experienced some of the largest crashes in returns. When volatility managing the momentum strategy, the excess kurtosis drops from 18.24 to 2.68 and the left skew from -2.47 to -0.42, diminishing negative portfolio returns. Hence, volatility management might reduce the negative skewness of investment strategies, where one limits investments in risky times without decreasing average returns (Barroso & Santa-Clara, 2015).

Moreira and Muir (2017) prove that volatility managed factor strategies generate higher alphas and Sharpe ratios for a selection of factors: market, value, momentum, profitability, return on equity, investment, betting-against-beta factors in equities, and currency carry trade. We investigate whether volatility management is as suitable for the equity duration strategy as it has proven to be for other factors.

2.2.2 Volatility Management Applied to Equity Duration

To create a volatility managed SML strategy, we follow Moreira and Muir's (2017) methodology. The SML portfolio is scaled by the realized variance from the previous month; thus, variance can be easily estimated by only relying on historical data. The approach is based on the discovery that although returns are not easily predicted, variance allows for greater predictability. As can be seen in equation *(1),* we compute daily excess returns, SML_{d}, in which we buy the equal amount of the Short duration portfolio, as we sell of the Long duration portfolio, making this a net-zero investment strategy.

$$SML_{d} = r_{S,d} - r_{L,d} \tag{1}$$

Based on the predictability of variance, we use the previous month's realized variance as our prediction of the current month's variance. The previous month's realized variance is calculated by the sum of squared daily variations in return of the SML portfolio, $\hat{\sigma}_m^2(SML)$, and is given by

$$\hat{\sigma}_m^2(SML) = \sum_{d=1/td}^{1} \left(SML_{m+d} - \frac{\sum_{d=1/td}^{1} SML_{m+d}}{td_m} \right)^2 \tag{2}$$

where *td* is the number of trading days in the month[10], *m.* The monthly standard deviation of our strategy is then used to scale our investment strategy by a target variance, *c*. Moreira and Muir (2017) choose *c* so that their volatility managed strategy has the same standard deviation as the plain strategy and argue that the choice of target volatility will not affect the

[10] Moreira and Muir (2017) generalize the formula for each month by dividing the sum of SML returns by 22 trading days. We have chosen to use the exact number of trading days in the month for increased accuracy.

strategy's Sharpe ratio. We first calculate the volatility managed strategy, SML_m^*, assuming *c* equals one, and thereafter solve equation *(3)* to find the value of *c*:

$$c = \frac{\sigma_{SML}}{\sigma_{SML^*}} \tag{3}$$

where σ_{SML} is the standard deviation of the plain SML strategy and σ_{SML^*} is the standard deviation of the volatility managed portfolio. The scaled strategy, SML_m^*, is then:

$$SML_m^* = \frac{c}{\hat{\sigma}_m^2} SML_m \tag{4}$$

We evaluate the performance of the volatility managed strategy by presenting time-varying strategy weights, descriptive statistics, and by evaluating the return of our volatility managed SML against the plain SML strategy and traditional asset pricing models.

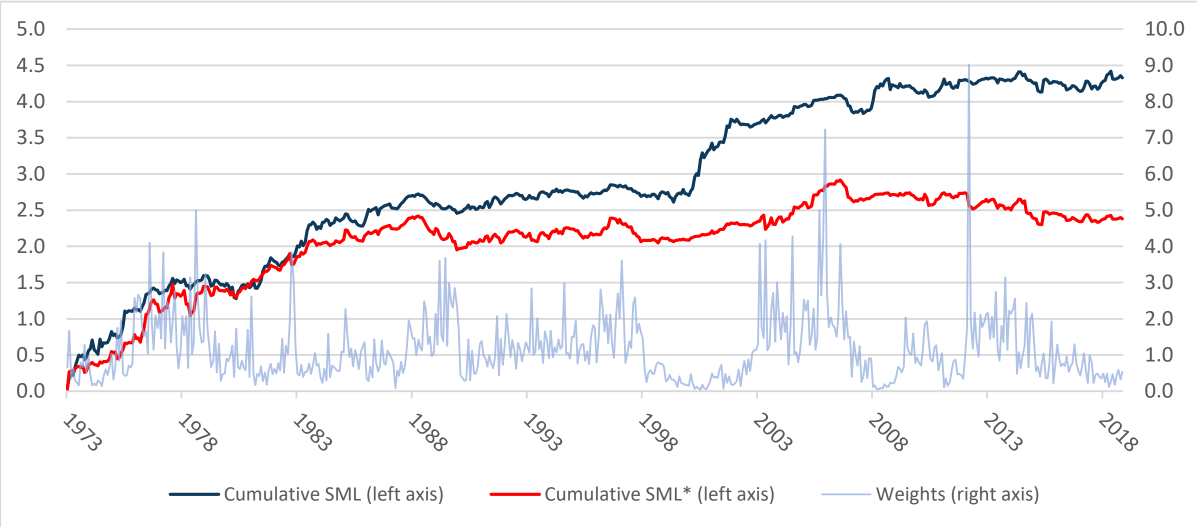
2.2.3 Results of the Volatility Managed SML Strategy

In this section we first inspect how volatility management scales exposure to our original strategy based on its realized volatility. Thereafter, we confirm that the difference between SML and SML* is not concentrated in any particular period of our sample, before determining if the difference in returns is significant.

Figure 1 illustrates time-varying strategy weights and the cumulative performance of SML and SML*. The time-varying strategy weight ($\frac{c}{\hat{\sigma}_m^2}$) can be interpreted as the extent to which we go into the SML strategy each month. The optimal weight is the trade-off between risk and return and can be seen as the attractiveness of the plain SML strategy. The strategy exposure weight, ranges from 0.04 to 9.02 times into the strategy, with an average weight of 1.15. The reason for the extreme values is that when realized volatility is high, we significantly reduce the exposure to the strategy to less than 1.00, while when volatility is low, we go into the strategy by more than 1.00. *Figure 1* also shows the dynamics between the cumulative returns and the time-varying strategy weights. Interestingly, the volatility managed strategy occasionally increases exposure to the original strategy in periods of negative returns (i.e. years after 1988). Additionally, in some periods of positive returns of SML (i.e. years after 1998), SML* takes on less exposure, hence the strategy misses out on some of the most positive performance periods of the equity duration strategy. Overall, the volatility managed

Figure 1:
Cumulative Performance and Time-varying Strategy Weights

The figure illustrates the cumulative returns (left axis) of the value weighted SML and SML, in addition to the monthly strategy weights (right axis) of SML*. The SML strategy buys Short duration firms and sells Long duration firms daily from July 1973 to 2019, and is formed every June of year t-1 (year t starting in July) based on duration estimates from Gonçalves (2021, 3). Following Moreira and Muir* (2017), *the volatility managed SML uses the realized variance of the previous month to scale its monthly exposure to SML. The figure shows monthly cumulative returns and time-varying strategy weights, starting in August 1973 due to one month of variance prediction.*



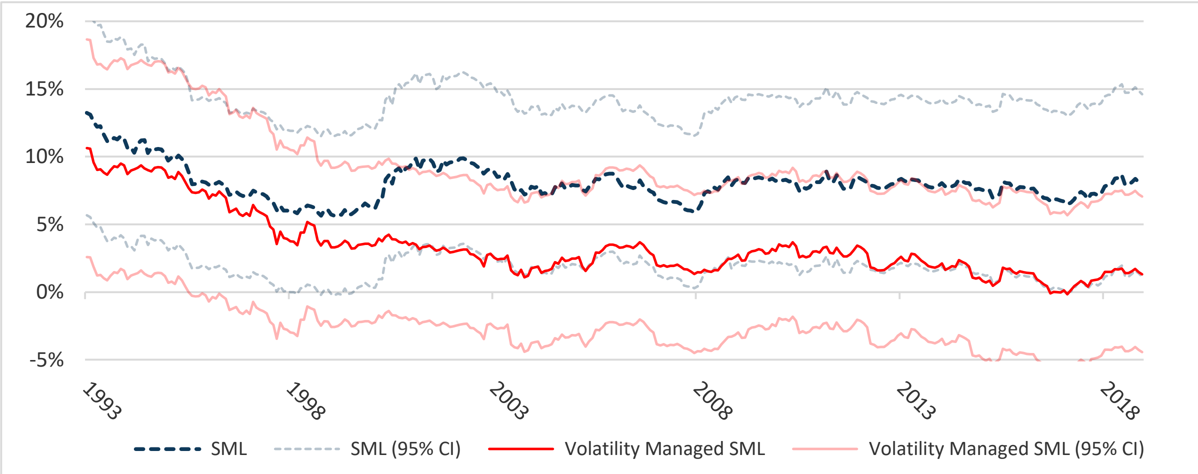
strategy performs poorly compared to the original strategy. However, its poor performance appears to be attributable to a few narrow periods of lower returns. To determine whether the difference between SML and SML* is due to these few instances, we inspect a 20-year rolling window of returns.

Figure 2 shows the 20-year cumulative returns of SML and SML* and confirms that the strategies' returns are not concentrated in a particular period. In *Panel A,* we see that in most periods we cannot reject the null hypothesis that the value weighted SML* premium is zero at a 95% confidence level, while for SML the opposite is true. In *Panel B*, we observe that the equal weighted SML* generates returns close to SML in early years of the 20-year rolling window of returns, but towards the end of the sample we cannot reject that the SML* premium is zero at a 95% confidence level. Furthermore, as the figure indicates that SML performs better that SML* on a 20-year rolling window, it demonstrates that the poor performance of SML* is long-lived and consistent in our sample period, and not due to differences in returns in a particular period, like the visual analysis of *Figure 1* would indicate.

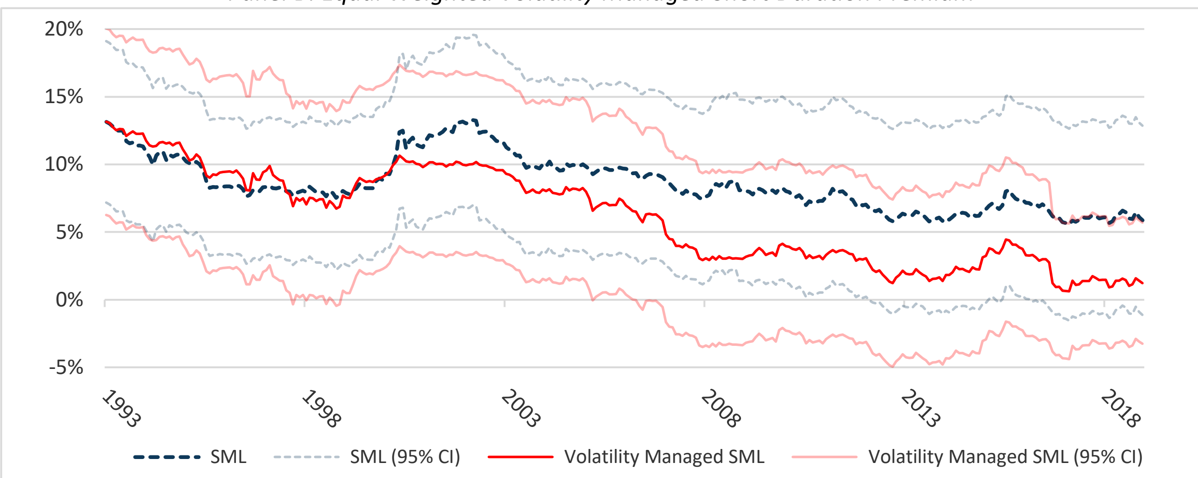
Figure 2:
Periodical Performance of Volatility Managed SML

The graphs show the 20-year rolling window of annualized returns (x 12) from July 1993 to June 2019 for value weighted (Panel A) and equal weighted (Panel B) strategies. A 20-year rolling window shows the cumulative return investors would earn when holding a portfolio for 240 months. The SML strategy buys Short duration firms and sells Long duration firms daily from July 1973 to 2019. The value weighted portfolio is formed every June of year t-1 (year t starting in July), while the equal weighted portfolio is formed at the end of every month. We use Gonçalves' (2021, 3) duration estimates. Following Moreira and Muir (2017), *the volatility managed SML uses the realized variance of the previous month to scale its monthly exposure to SML. The 95% confidence intervals for SML and SML* are reported in translucent lines.*

Panel A: Value Weighted Volatility Managed Short Duration Premium



Panel B: Equal Weighted Volatility Managed Short Duration Premium



In *Figure 2, Panel A,* we have frequent observations where the premium of SML* is on the border of a 95% confidence interval for the premium of SML. Therefore, we test whether volatility managing SML produces significantly lower returns than SML. To inspect if certain characteristics of the SML makes it unsuited for volatility management, we also investigate the characteristics of factor strategies that have undergone volatility management in previous studies.

Table 4:
Descriptive Statistics of Investment Strategies

The table summarizes key characteristics of the value weighted SML and SML, and various other investment strategies based on returns from August 1973 until June 2019. The first row (SML) is the benchmark to measure the performance of the second row (SML*). The SML strategy buys Short duration firms and sells Long duration firms daily from July 1973 to 2019, and is formed every June of year t-1 (year t starting in July) based on duration estimates by Gonçalves (2021, 3). Following Moreira and Muir* (2017), *the volatility managed SML uses the realized variance of the previous month to scale its monthly exposure to SML. Summary statistics for SML and SML* are based on daily return data, which are first averaged to monthly returns, then annualized*[11]. *Factor strategies are based on average annualized monthly returns: the market (MktRF), size (SMB), book-to-market (HML), profitability (RMW), investments (CMA), and momentum (MOM). The first five factors are factors from Fama-French (1996, 2015) and momentum is from Jegadeesh & Titman (1993). The strategies' skewness refers to the negative versus positive concentration of observations. The strategies' kurtosis refers to the extent to which observations are concentrated around their mean. Excess market return (MktRF) is market return minus the U.S. monthly T-bill rate. All strategies' monthly returns (x 12), standard deviations (x* $\sqrt{12}$*) and Sharpe ratios are annualized. The t-test examines the difference in returns of SML* and SML.* t_{stat} *is reported in parentheses. Stars indicate the significance level: *p < 0.10, ** p < 0.05, *** p < 0.01.*

Portfolio	Strategy	Mean (%)	Std. dev. (%)	Sharpe Ratio	Skewness	Kurtosis
Value weighted	SML	9.43	15.62	0.60	0.64	6.04
	SML*	5.19	15.62	0.33	-0.01	8.32
	($t_{SML*-SML}$)	(-2.46)***				
Equal weighted	SML	8.65	14.43	0.60	0.43	6.03
	SML*	7.07	14.43	0.49	0.79	9.50
	($t_{SML*-SML}$)	(-0.93)				
Factor Strategies	MktRF	7.05	15.73	0.45	-0.58	5.03
	SMB	2.72	10.33	0.26	0.35	7.19
	HML	3.63	10.04	0.36	0.17	4.96
	RMW	3.32	8.00	0.42	-0.43	15.43
	CMA	3.74	6.71	0.56	0.39	4.54
	MOM	7.53	15.07	0.50	-1.36	13.72

Table 4 reports the characteristics and performance of the original and volatility managed SML and various well-established factor strategies. Applying volatility management to the SML strategy offers surprising results. In *Table 4*, we find that after volatility managing the strategy, the mean annualized return is reduced by 4.24 percentage points, yielding a reduced Sharpe ratio of 0.27. For equal weighted portfolios, we fail to reject the null hypothesis that SML and SML* produce similar returns. However, visual analysis of *Figure 1* and *2,* and a negative difference in average returns between original and volatility managed SML in *Table*

[11] The deviation from mean returns presented in 2.1.3 Replication Results of 9.3% and 8.8% return for value weighted and equal weighted portfolios, respectively, is a result of discrepancies in the treatment of delisting restrictions when handling daily data as opposed to monthly data.

4, suggests that volatility management does not improve SML, also for equal weighted portfolios. The reduced risk-adjusted returns of SML* make us question whether volatility managing SML is as efficient as it has proven to be for other factors (Moreira & Muir, 2017) (Barroso & Santa-Clara, 2015).

One possible explanation for the contrasting effect of volatility managing the SML, as compared to momentum, for which volatility management has proven successful, is that the strategies' skewness differs greatly. When Barroso and Santa-Clara (2015) volatility manage momentum, they correct a significant left skew, meaning they eliminate some of the largest crashes of the strategy. In fact, the positive alphas[12] found in previously volatility managed factor strategies by Moreira and Muir (2017), seem to have a close relationship to the skewness we find in our data sample, presented in *Table 4*. Factor strategies with a negative skewness – MrktRF, RMW, and MOM – all return high, positive, and statistically significant alphas for their volatility managed strategies by Moreira and Muir (2017). Additionally, the factor strategies with the highest positive skewness – SMB and CMA – both have negative, though statistically insignificant alphas for their volatility managed strategies. Complementing this discovery, we find that volatility managing the equity duration strategy removes some of the right skew and increases kurtosis. Eliminating the positive skewness for SML (from 0.64 to -0.01 for the value weighted portfolio), reduces return in some of the best performing months of the strategy. This shows the opposite effect of what we desire from volatility management; namely that it reduces the worst performing months of an investment strategy. The reduced right skew could indicate why we are left with lower average returns for SML* than for SML.

To isolate the premium from managing the volatility of SML, we perform factor regressions on the volatility managed duration strategy. We use the original duration strategy, SML, and traditional asset pricing models as a benchmark to distinguish the effect of volatility management from other factors.

[12] Volatility managed factors are regressed on original factors and the Fama-French three factor model (Moreira & Muir, 2017). Annualized alphas and respective standard errors presented are as follows: MrktRF (5.45%, 1.56), RMW (3.18%, 0.83), MOM (10.52%, 1.60), SMB (-0.33%, 0.89), and CMA (-0.01%, 0.68).

Table 5:
Factor Regressions of Volatility Managed SML

The table presents the portfolio returns and factor loadings of the volatility managed SML strategy, SML. The SML strategy buys Short duration firms and sells Long duration firms daily from July 1973 to 2019. The value weighted portfolio is formed every June of year t-1 (year t starting in July), while the equal weighted portfolio is formed at the end of every month. We use duration estimates by Gonçalves (2021, 3). Following Moreira and Muir* (2017)*, the volatility managed SML uses the realized variance of the previous month to scale its monthly exposure to SML. Each column represents a regression of SML* on a different set of investment strategies. We include monthly returns of explanatory variables: the market (MktRF), size (SMB), book-to-market (HML), profitability (RMW), investments (CMA), momentum (MOM) and duration (SML). The first five factors are factors from Fama-French (1996, 2015) and momentum is from Jegadeesh & Titman* (1993)*. Excess market return (MktRF) is the market return minus the U.S. monthly T-bill rate. Alphas are annualized and reported in percentages. P-values are in brackets and stars indicate the significance level: *p < 0.10, ** p < 0.05, *** p < 0.01.*

	Value weighted				Equal weighted		
SML*	CAPM SML	FF3 SML	FF5 MOM SML	SML*	CAPM SML	FF3 SML	FF5 MOM SML
SML	0.75***	0.78***	0.79***	SML	0.68***	0.70***	0.79***
	[0.00]	*[0.00]*	*[0.00]*		*[0.00]*	*[0.00]*	*[0.00]*
MktRF	0.09***	0.08**	0.05	MktRF	-0.01	0.00	-0.02
	[0.00]	*[0.02]*	*[0.13]*		*[0.81]*	*[0.96]*	*[0.50]*
SMB		0.02	-0.01	SMB		-0.05	-0.13***
		[0.71]	*[0.86]*			*[0.26]*	*[0.01]*
HML		-0.14***	-0.06	HML		-0.02	-0.02
		[0.01]	*[0.42]*			*[0.66]*	*[0.75]*
RMW			-0.10	RMW			-0.27***
			[0.11]				*[0.00]*
CMA			-0.18*	CMA			-0.17*
			[0.07]				*[0.07]*
MOM			0.00	MOM			-0.08**
			[0.90]				*[0.01]*
Alpha (%)	-2.50	-2.24	-1.39	Alpha (%)	1.23	1.26	3.03*
	[0.13]	*[0.17]*	*[0.41]*		*[0.45]*	*[0.44]*	*[0.06]*

Table 5 reports the regressions of SML* on traditional asset pricing models and SML to show relative improvements of volatility management in the alpha of SML*. Similarly to what we found in *Table 4,* the results of the regressions in *Table 5* rebut our hypothesis of an improvement in the performance of SML. For the value weighted portfolios, the regressions return negative but insignificant alphas, and we fail to accept that volatility managing SML leads to a significant change in the returns of the original strategy. The coefficients of the plain SML are significant at the 1% level for all regressions and between 0.75 to 0.79, meaning that the excess return is strongly explained by short minus long durations portfolios, as

expected. We also observe a positive coefficient on the market, in which all regressions have a significant coefficient on a 5% level. This finding suggests that when the market return is positive, volatility managing SML might yield a positive premium.

The equal weighted SML*, delivers a positive significant alpha for the Fama-French five factor plus momentum and SML regression of 3.03% at a 10% level, contrastingly to value weighted SML*. The strategy's excess returns can partly be explained by the coefficients of the factors. Equal weighted SML* bets on large firms (negative SMB), weak profitability (negative RMW), aggressive investments (negative CMA) and low momentum (negative MOM), all factors significant at a 10% level. The positive alpha of the equal weighted portfolio relative to value weighted portfolios, might be explained by an overinvestment in small firms. Small firms are generally more volatile than large firms. It is therefore natural that volatility managing these portfolios, is more efficient in hedging against volatility. We will therefore focus our analysis on results from the value weighted regressions.

The results presented in this section indicate that volatility managing the SML strategy yields a poor risk-return tradeoff. This is surprising given the proven effectiveness of volatility managing traditional asset pricing models (Moreira & Muir, 2017) (Barroso & Santa-Clara, 2015). Analysis has suggested that the poor performance of SML* might be due to distinct characteristics of the SML strategy, such as positive skewness. We attempt to confirm this suspicion by ruling out other possible explanations in our model.

So far, we have applied Moreira and Muir's (2017) measure to predict variance. For the following section we investigate whether weak results are due to 1) poor predictions of portfolio variance, or because 2) volatility management is not efficient for an equity duration strategy.

2.2.4 Inspecting the Predictability of Variance

In section *2.2.3* we find that the volatility managed short duration premium strategy is not as lucrative as expected. This leads us to question how efficient the volatility measure is at predicting volatility. In examining the efficiency of Moreira and Muir's (2017) volatility measure, we introduce an alternative measure by Barroso and Santa-Clara (2015) for comparable analysis. In short, Barroso and Santa-Clara's methodology scales the SML

Table 6:
Testing the Effectiveness of Variance Predictions

The t-tests presented determine if there is a difference between the predicted and realized variance of SML. The test is based on monthly variances from August 1973 to June 2019 for Moreira and Muir (2017), and from January 1974 until June 2019 for Barroso and Santa-Clara (2015)*. The SML strategy buys Short duration firms and sells Long duration firms daily from July 1973 to June 2019, and is formed every June of year t-1 (year t starting in July) based on duration estimates by Gonçalves (2021, 3). Following Moreira and Muir* (2017)*, the predicted variance is based on the realized variance of the previous month. In Barroso and Santa-Clara's* (2015) *approach, the predicted variance is based on realized variance from the previous six months. The values in the table represent the difference in mean between predicted- and actual variance for value weighted and equal weighted portfolios.* t_{stat} *is reported in parentheses.*

Methodolgy	Value weighted	Equal weighted
Moreira & Muir	-9.58E-07 *(-0.01)*	8.50E-07 *(0.02)*
Barosso & Santa-Clara	3.89E-06 *(0.22)*	1.70E-06 *(0.13)*

duration portfolio by the realized variance from the last six months. Based on square returns of the SML strategy from the previous 126 trading days, we estimate the daily variance of our strategy, which is then transformed into monthly averaged estimates and given by:

$$\hat{\sigma}^2_{SML,m} = \frac{21}{126} \sum_{d=1}^{126} r^2_{SML,d} \tag{9}$$

To test the effectiveness of the two variance predictions of the different methodologies, we utilize a t-test to see if there is a statistically significant difference between the predicted and the actual variance of each approach to volatility. The null hypothesis is that the predicted variance minus the actual variance equals zero.

Table 6 shows the difference between the predicted and the actual variance per month, for value- and equal weighted portfolios, following the approaches from Moreira and Muir (2017) and Barroso and Santa-Clara (2015). When checking if the difference between the predicted and the actual variance equals zero, we find low t-statistics for all four tests conducted. Therefore, we cannot reject the null hypothesis that predicted variance is equal to actual variance. We conclude that Moreira and Muir's (2017) method for variance prediction is satisfactory and cannot be identified as the explanation for poor risk-adjusted returns when volatility managing the short duration premium strategy. Therefore, we further investigate whether it is the characteristics of SML that makes volatility management fail to improve risk-adjusted returns.

2.2.5 Volatility Management in Good Times and Bad Times

In the previous sections we find that volatility management is not as efficient for the equity duration strategy as hypothesized. We conclude that the volatility measure from Moreira and Muir (2017) is appropriate when predicting volatility for the duration strategy[13]. This leads us to our second hypothesis; that volatility management is not as effective in hedging the SML portfolio as it has proven to be for other investment strategies. Barroso and Santa-Clara (2015) find that the benefits of risk managing momentum are particularly strong in turbulent times. Hence, we will further test our hypothesis by inspecting the most extreme crashes and upturns of our strategy and the market. First, we will introduce the density function of monthly returns of SML and SML*. Second, we study a low- and a high volatility period of the SML strategy. Last, we test the performance of SML* and SML based on three definitions of good times and bad times.

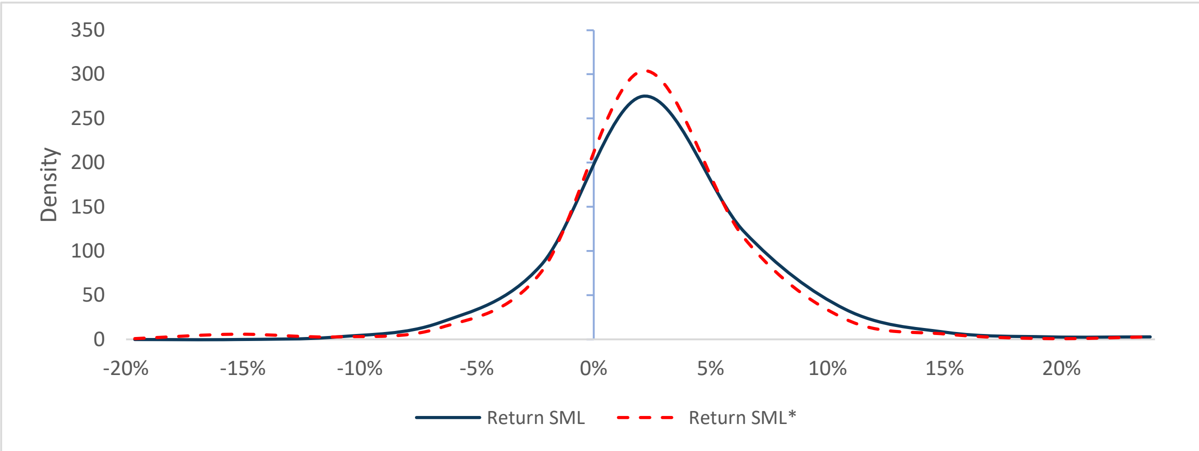
Figure 3 shows the distribution of the performance of SML and SML*. *Panel B* and *C* highlight the periods with the most substantial crashes and booms, respectively. As found in *Table 4* in section *2.2.3*, the kurtosis of the value weighted SML increases from 6.04 to 8.32 and skewness is reduced from 0.64 to -0.01 after volatility managing SML. In *Figure 3, Panel A*, we clearly observe a higher density around the mean of SML* than for SML. In *Panel B,* the higher density of negative SML* returns indicates that we experience low volatility, and therefore higher SML* exposure weights, in some periods of negative returns. Therefore, some of the largest crashes for the plain SML strategy become even more disadvantageous in the volatility managed strategy. *Panel C* present the density of periods with monthly returns above 5%, in which we observe lower density for most return bins for SML* compared to SML, signaling high volatility in periods of high returns. Hence, we conclude that the reduced positive skewness has removed some of the greatest positive returns (reduced right tail) while also giving more weight to SML in periods of low returns (increased left tail). This confirms our

[13] As results in Table 6 indicate that Moreira and Muir’s (2017) methodology predicts volatility more accurately than that of Barroso and Santa-Clara (2015), we base remaining analysis on Moreira and Muir’s measure. Similar analysis based on Barroso and Santa-Clara’s measure is available upon request.

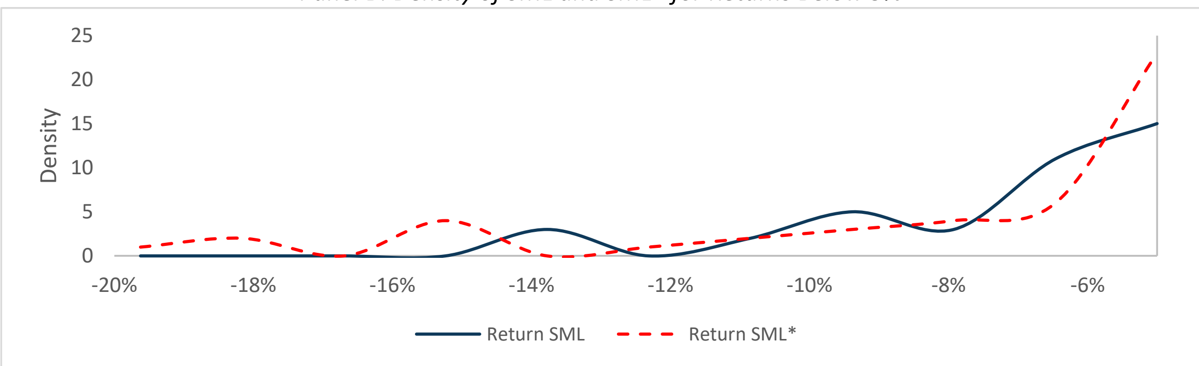
Figure 3:
Density of Returns in Good and Bad Times

The figures present the density function of the volatility managed strategy (SML) and plain duration strategy (SML) from August 1973 to June 2019. The value weighted SML strategy buys Short duration firms and sells Long duration firms daily, and is formed every June of year t-1 (year t starting in July) based on duration estimates by Gonçalves (2021, 3). Following Moreira and Muir* (2017), *the volatility managed SML uses the realized variance of the previous month to scale a monthly exposure to SML. The x-axis shows monthly returns. Panel B shows the density of returns below -5% (left tail), while Panel C show the density of returns above 5% (right tail).*

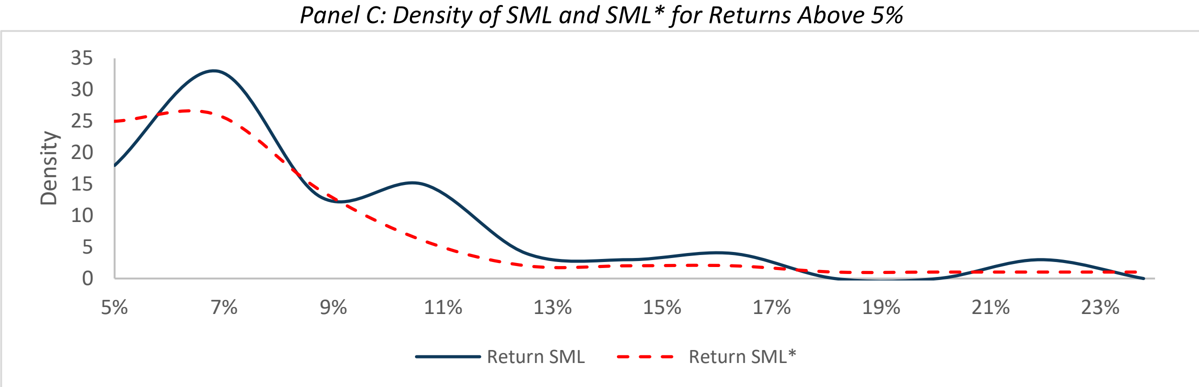
*Panel A: Density of SML and SML**



Panel B: Density of SML and SML for Returns Below 5%*



Panel C: Density of SML and SML for Returns Above 5%*

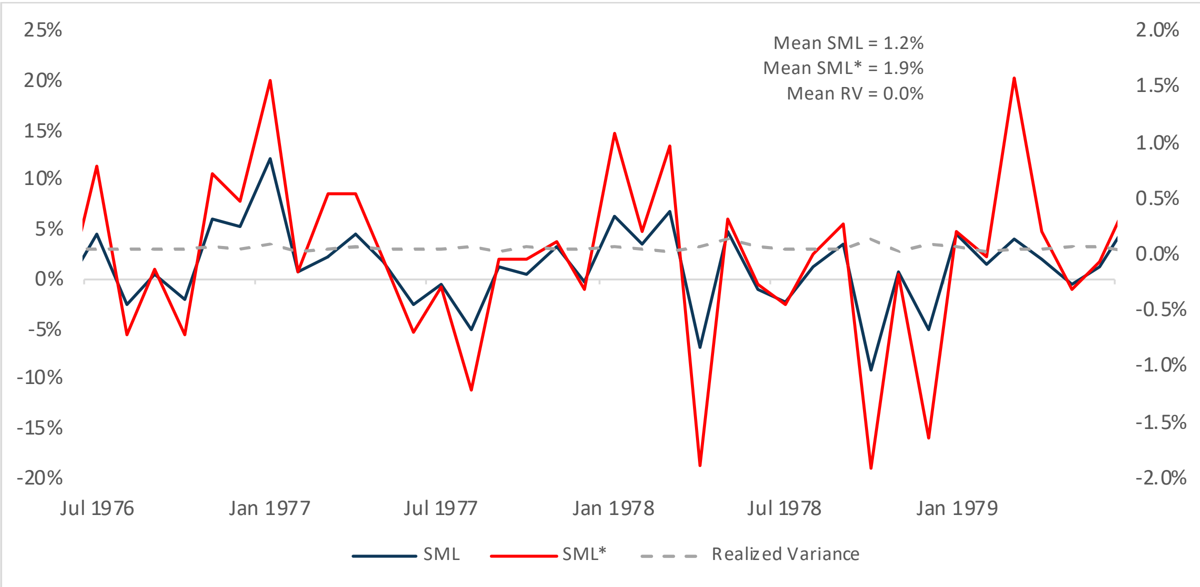


second hypothesis, that volatility management is unaligned with the strategy's characteristics. In the remaining of the section, we investigate how strategy characteristics prevents SML* from yielding improved risk-adjusted returns.

Figure 4:
Zooming into Low and High Volatility Periods

The figure plots the returns of the volatility managed strategy (SML) and plain duration strategy (SML), as well as the realized variance of SML. The SML strategy buys Short duration firms and sells Long duration firms daily, and is formed every June of year t-1 (year t starting in July) based on duration estimates by Gonçalves (2021, 3). Value weighted portfolios are created every June from 1973 to 2018. Following Moreira and Muir* (2017)*, the volatility managed SML uses the realized variance of the previous month to scale monthly exposure to SML. Presented in Panel A, July 1976 to June 1979 is used as an example of a low volatility period. Presented in Panel B, July 1999 to June 2002 is used as an example of a high volatility period. The figures show monthly return (left y-axis) and variance (right y-axis).*

Panel A: Low Volatility Period (July 1976 - June 1979)



Panel B: High Volatility Period (July 1999 - June 2002)

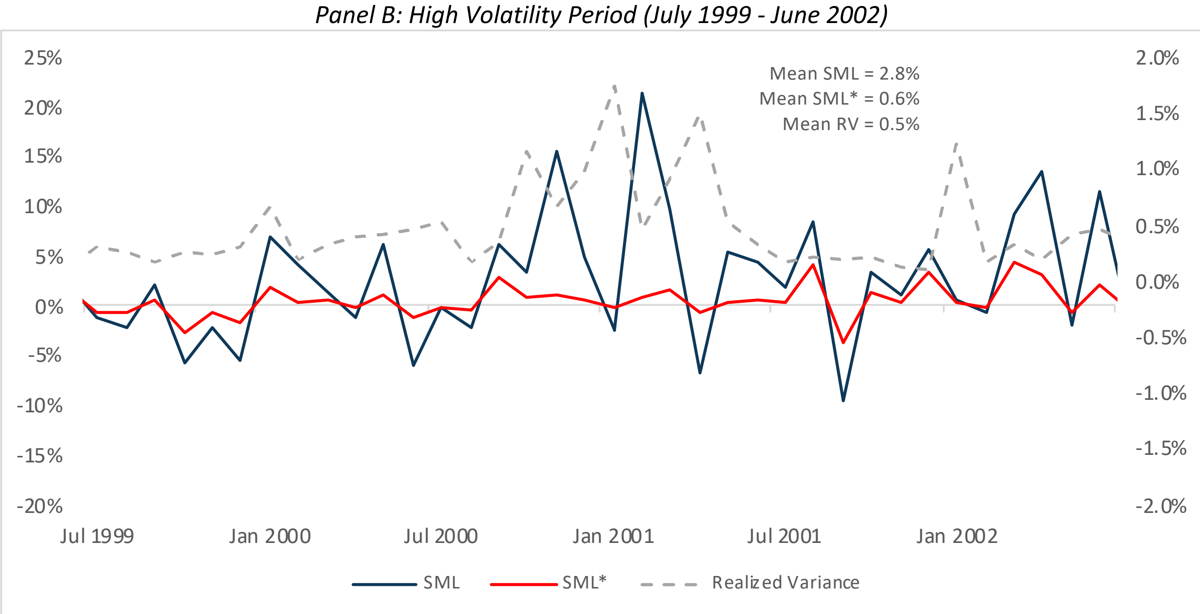


Figure 4 displays the performance of SML* and SML for a low volatility period (*Panel A*), and a high volatility period (*Panel B*). These periods have been selected as examples as July 1976 to June 1979 is a period of consistently high strategy exposure, and July 1999 to June 2002 is

a period of consistently low strategy exposure, as can be seen in *Figure 1*. Not surprisingly, we observe in *Figure 4* that when the volatility is low (*Panel A*), the SML* goes more than 100% into the SML strategy. This results in more extreme returns than SML for both positive and the negative outputs. In *Panel B*, SML* shows less extreme returns than SML, as we are in a period of high volatility, where we invest less in the strategy. Hence, *Panel A* and *B* proves that the model is technically working.

In addition to validating the technicality of the SML*, *Figure 4* also shows that in this period of low volatility (*Panel A*), SML provides relatively low returns, and in this period of high volatility (*Panel B*), SML provides relatively high returns. Increasing exposure to SML when volatility is low, therefore makes investors increase their position in SML when returns are low. Similarly, decreasing exposure to SML when volatility is high, makes investors miss out in periods with high returns. The fact that the relationship between volatility and returns is not inverse, might indicate that volatility management is less appropriate for the short duration premium than for other investment strategies, as found in Moreira and Muir (2017). The findings from *Figure 4* contradict the basis of the functionality of volatility management, as laid out by Moreira and Muir (2017). When applying the volatility management strategy, we generally increase risk-taking in periods with low returns and reduce risk-taking in periods with high returns.

One possible explanation for SML's positive relationship between volatility and returns is that 1) SML is countercyclical to the market, and 2) studies have found that, generally, market volatility is high when market returns are low (Muir, 2017). As Gonçalves (2021) explains; when the market crashes, the relatively higher sensitivity of long duration portfolios to lower interest rates, makes long duration portfolios attractive to investors. Long duration portfolios therefore require a relatively lower risk premium, and the SML premium is ultimately greater in bad economic times. As there has proven to be high market volatility in crashes (Muir, 2017), and we argue that SML return is high when the market is crashing, it stands to reason that we miss out on the greatest peaks of return when scaling our strategy to the inverse of volatility. Given the findings in *Figure 3* and *Figure 4,* and the novel link between SML, the market, and volatility management, we explore the relationship between SML and SML* in the SML strategy's and the market's high and low return periods further.

Table 7:
Inspecting Good and Bad Times

The table reports the difference in mean between monthly returns of the volatility managed and plain SML (SML - SML) in good and bad times, as defined by three definitions. The SML strategy buys Short duration firms and sells Long duration firms daily from July 1973 to 2019, and is formed every June of year t-1 (year t starting in July) based on duration estimates by Gonçalves (2021, 3). Following Moreira and Muir* (2017)*, the volatility managed SML uses the realized variance of the previous month to scale a monthly exposure to SML. "Sample" refers to the top decile and lowest decile of performance periods for the SML strategy. "Market" refers to the highest and lowest decile of the market risk-free return as defined by Fama-French. "NBER" refers to the National Bureau of Economic Research's defined periods of recessions, retrieved from the publicly available dataset "US business cycle Expansions and Contractions"* (NBER, 2022)*. Significant t-tests at the 5% level are reported in bold.* t_{stat} *is reported in parentheses. Stars indicate the significance level: *p < 0.10, ** p < 0.05, *** p < 0.01.*

SML - SML*	Sample (SML)	Market	Recession
Good times	**-3.86 %** *(-4.74)****	0.73 % *(1.15)*	
Bad times	0.60 % *(0.80)*	**-2.29 %** *(-3.30)****	-0.97 % *(-1.76)**

Table 7 shows the difference in monthly annualized returns between SML and SML*. For the top 10% SML returns, we reject the null hypothesis that SML* is equal to plain SML. We see that volatility managing SML leads to significantly worse returns in the best performance periods of the strategy. However, SML* provides fewer extreme returns in the worst times of the strategy, though the difference is statistically insignificant. These findings indicate that the volatility management function provides a technical buffer to extreme return values but is less efficient in its bad times than in its good times.

Furthermore, we find that volatility managing SML leads to significantly worse returns (-2.29 percentage points) when the market is performing in the bottom decile of our sample period. Supporting this finding, for periods defined by NBER as recessions, we reject the null hypothesis at a 10% significant level, validating that volatility managing SML leads to significantly lower returns in recessions. It is worthwhile to note that SML is countercyclical – in the market's best performing months, both SML and SML* provide negative monthly returns (-1.52% and -0.79%, respectively), and in the market's worse performing months, both provide positive monthly returns (4.06% and 1.77%, respectively). The same countercyclicality can be seen in recessions – both SML and SML* provide positive monthly returns (1.75% and 0.78%, respectively). This finding is a possible explanation for why SML sees low returns in low volatility periods, and high returns in high volatility periods, as discussed in analysis of *Figure 4.*

In this section, we argue that volatility management is not efficient for the equity duration strategy. We find that SML* yields lower risk-adjusted returns than SML and argue that one possible explanation might be the reduction of the significant positive skewness of SML. Additionally, and contrary to the grounds of volatility management, we find that SML often yields low returns in periods of low volatility, and high returns in periods of high volatility. Given the SML's skewness and cyclicality found in this section, we suggest that there is no improvement in the short duration premium as volatility management is poorly aligned with its characteristics.

2.2.6 Portfolio Adjustments

In this section, we make two adjustments to our original equity duration portfolios to confirm the reliability of our volatility management results. First, we seek to reduce portfolio noise by restricting our data sample to firms that are consistently allocated to the same portfolio. Second, we argue that yearly rebalancing of the value weighted SML strategy could be more aligned with the reality of investors' transaction costs. We update our volatility managed SML with a consistent and yearly rebalanced portfolio. In this section, we restrict our analysis to value weighted portfolios, as defined in *2.1.2.1.*

2.2.6.1 Consistent Portfolios

The purpose of the first adjustment is to explore whether the short duration premium holds when increasing the consistency in the portfolio allocation of firms. Gonçalves' (2021) measure of equity duration gathers a significant short duration premium, but we observe a significant amount of noise when allocating firms into equity duration portfolios. Although equity duration is a more fluid approximation than bond duration, there may be benefits to increase the consistency in the portfolio allocation of a firm. Reducing noise from sudden, short-lived, and considerable changes in a firm's accounting and stock return data, should not eliminate the existence of the short duration premium given that equity duration really is the firm characteristic that motivates the premium.

To decrease random noise, we limit our data sample to those firms that are consistent in their allocation to duration portfolios. For any given year *(t)*, we only keep firms that are allocated into the duration portfolio that is either the same *(pX),* one higher *(pX+1)*, or one lower

Table 8:
Consistent Data Sample

The table provides a summary of the number of portfolios each firm is allocated to in their lifetime before and after adding the restriction of consistency. The requirement of the Consistent Data Sample is that a firm at time t must have been allocated to the same duration portfolio (pX), or one portfolio above (pX+1), or one portfolio below (pX-1), in the two previous years (t-1 and t-2). As a consequence, our sample is limited to observations between July 1975 and June 2019. Portfolio Allocations (#) indicates the number of different duration portfolios one firm appears in throughout the firms' lifetime. Firms (#) is the number of firms observed for each of the Portfolio Allocations (#). Cumulative Firms (%) represent the cumulative distribution of firms, starting from the firms that appear in the highest number of different portfolios. We use Gonçalves' (2021, 3) duration estimates. The portfolios are value weighted, as described in 2.1.2.1.

Consistent Data Sample			Original Data Sample		
Portfolio Allocations (#)	Firms (#)	Cumulative (% of Firms)	Portfolio Allocations (#)	Firms (#)	Cumulative (% of Firms)
10	2	0 %	10	158	1 %
9	12	0 %	9	405	5 %
8	29	1 %	8	676	10 %
7	90	2 %	7	914	17 %
6	207	4 %	6	1030	26 %
5	401	9 %	5	1248	36 %
4	684	18 %	4	1424	47 %
3	1147	33 %	3	1675	61 %
2	2331	63 %	2	2072	78 %
1	2907	100 %	1	2744	100 %
Average: 2.3	Sum: 7810		Average: 3.8	Sum: 12346	

(pX-1), across both of the two previous years *(t-1 and t-2).* For example, if a firm is allocated to portfolio 7 *(p7)* in year *t* based on Gonçalves' duration measure, we only keep the firm if it is allocated to portfolios *p6, p7*, or *p8* in both year *t-1* and year *t-2.*

Table 8 provides an overview of the number of different portfolio allocations of each firm in the original and consistent data sample. We find that our consistent data sample greatly reduces the inconsistency of the original value weighted data sample[14]. Firms in our original data sample have an average life span of 9.5 years[15] and are allocated to 3.8 different duration portfolios on average. The allocation of the most consistent 50% of firms is reduced from three to two different portfolio allocations. Looking at the extremes, the firms allocated to

[14] See Appendix 5 for the performance of equal weighted, consistent portfolios.

[15] The average life span of 9.5 years only includes years where firms in the data sample fulfil Gonçalves' (2021) restrictions. Firms are required to have two previous years of acceptable accounting data in Compustat for backfilling concerns.

Table 9:
Performance of Consistent Duration Portfolios

*The table shows the excess return of value weighted duration portfolios and the short duration premium for our consistent and original data samples. Value weighted duration portfolios are created every June (1973 to 2018) based on duration estimates by Gonçalves (2021, 3). The requirement of the Consistent Data Sample is that a firm at time t must have been allocated to the same duration portfolio (pX), or one portfolio above (pX+1), or one portfolio below (pX-1), in the two previous years (t-1 and t-2). As a consequence, our sample is limited to observations between July 1975 and June 2019. Panel A shows annualized average monthly returns (x 12) and Sharpe ratios (x $\sqrt{12}$). In Panel A, t_{stat} reported in parentheses confirm whether there is a statistical difference between the returns of the Short and the Long duration portfolios. Numbers in bold are discussed in specificity in the analysis. Panel B reports the difference in annualized average premiums of the original and consistent SML. t_{stat} reported in parentheses confirm whether there is a statistical difference between the short duration premiums of the consistent and original portfolios. Stars indicate the significance level: *p < 0.10, ** p < 0.05, *** p < 0.01.*

Panel A: Consistent Portfolio Performance

Duration decile	Consistent Data Sample		Duration decile	Our Original Portfolios	
	Excess return	Sharpe ratio		Excess return	Sharpe ratio
Short	11.3 %	0.59	Short	13.0 %	0.71
2	12.2 %	0.73	2	13.2 %	0.76
3	13.1 %	0.74	3	13.6 %	0.78
4	**14.1 %**	**0.82**	4	12.8 %	0.74
5	11.5 %	0.72	5	10.7 %	0.64
6	8.8 %	0.55	6	9.9 %	0.58
7	8.8 %	0.56	7	9.5 %	0.54
8	7.6 %	0.44	8	8.5 %	0.45
9	6.4 %	0.33	9	6.6 %	0.32
Long	4.7 %	0.23	Long	4.2 %	0.18
SML	6.6 %	0.42	SML	8.8 %	0.60
(t_{SML})	(5.25)***		(t_{SML})	(3.95)***	

Panel B: Testing the Difference

			Difference	t-value
$SML_{Consistent}$	-	$SML_{Original}$	-2.2 %	(-1.36)*

either 8, 9, or 10 different portfolios, decreases from 10% to only 1% in the consistent data sample. The average portfolio allocation is reduced to firms appearing in 2.3 different portfolios. As a result of the restriction, the consistent portfolio contains of 63% of the firms that appear in the original data sample.

Table 9 reports the annualized returns and Sharpe ratios of the decile portfolios and SML. The short duration premium is reduced by 2.2 percentage points when limiting our data sample to consistent firms. Interestingly, when we look at consistent portfolios, we do not find the same monotone and steady decrease in returns from the Short to the Long portfolio that we see in the original data sample. The return of the consistent portfolios increases steadily until portfolio 4, and then returns to its normal state of decreasing returns towards the Long portfolio[16]. One possible explanation might be that firms experiencing the odd year of high returns are placed in the short duration portfolios, elevating average excess returns in these portfolios. Taking more than one year of data into account, firm characteristics might not place these firms in the short duration portfolios. The peak in returns in the consistent portfolio, decile 4, is an interesting finding that we leave for future research.

When increasing consistency, there is a slight decrease in the SML premium. However, as the short duration premium persists and is significantly different from zero, we conclude that the short duration premium is robust to noise occurring in Gonçalves' (2021) equity duration measure. Next, we test whether the premium persists when decreasing the frequency of rebalancing.

2.2.6.2 Yearly Rebalanced Portfolios

To test the viability of the short duration premium in the face of frequent transaction costs, we adjust the "portfolio management" of our strategy. Gonçalves (2021) creates value weighted portfolios only once per year. As can be seen from equation *(5),* stock weights are determined by market equity, which is in turn fluctuating with stock prices in the open market. Therefore, there follows an assumption of continuous rebalancing of stocks to maintain weights as defined in June, constant for the next twelve months. The weight (w_{it}) per firm (*i*) at time *t* is determined by the number of stocks the investor holds (n_{it}) and the firms' stock price (P_{it}) over the total market equity in the investor's portfolio:

$$w_{it} = \frac{ME_{it}}{\sum_{i=1}^{n} ME_i} = \frac{n_{it} * P_{it}}{\sum_{i=1}^{n} ME_i} \tag{5}$$

The frequency at which investors rebalance their portfolio affects investors' net return through stock price fluctuations' effect on asset weights and transaction costs (Zilbering, Jaconetti, & Kinniry, 2015). First, keeping stock weights constant results in a systematic process of purchasing more of stocks that perform poorly and selling those that perform well.

[16] The peak in average return in portfolio 4 persists as we increase the strictness of the consistency restriction. Only keeping firms at time t that have been allocated to the same duration portfolio (pX), or one portfolio above (pX+1), or one portfolio below (pX-1), in the three previous years (t-1, t-2 and t-3), results in a peak of 10% return in portfolio 4.

Table 10:
Performance of Yearly Rebalanced Portfolios

The table presents the excess return and the short duration premium for value weighted yearly- and monthly rebalanced portfolios. The data sample runs from July 1973 to June 2019. Value weighted duration portfolios are created every June (1973 to 2018) based on duration estimates by Gonçalves (2021, 3). The table shows annualized average monthly return (x 12) and Sharpe ratios (x $\sqrt{12}$). t_{stat} is reported in parentheses and confirm whether there is a statistical difference between the returns of the Short and the Long duration portfolios.

Duration	Yearly rebalancing		Duration	Monthly rebalancing	
decile	Excess return	Sharpe ratio	decile	Excess return	Sharpe ratio
Short	12.8 %	0.67	Short	13.0 %	0.66
2	11.4 %	0.66	2	11.7 %	0.66
3	12.0 %	0.70	3	12.7 %	0.72
4	11.7 %	0.71	4	12.0 %	0.72
5	11.0 %	0.66	5	11.1 %	0.66
6	8.9 %	0.56	6	9.1 %	0.57
7	8.2 %	0.51	7	8.5 %	0.52
8	7.1 %	0.41	8	7.5 %	0.42
9	5.4 %	0.29	9	5.6 %	0.29
Long	3.9 %	0.19	Long	3.7 %	0.17
SML	9.0 %	0.59	SML	9.3 %	0.59
(t_{SML})	*(6.25)*		*(t_{SML})*	*(6.25)*	

In theory, this might result in lower returns. Additionally, constant rebalancing encompasses significant transaction costs, such as processing, tax, time, spread, and labor costs. Although transaction costs will not be evident in returns presented in this paper, an investor should be aware of this negative consequence of frequent rebalancing.

In *Table 10*, we decrease the frequency from monthly to yearly rebalancing to reduce the transaction costs of continuous repurchasing and selling of stocks. We would expect an increase in overall portfolio returns, as stocks that do well are allowed an increased weight in the value weighted portfolio for the next month. Interestingly, less frequent rebalancing yields lower returns for all portfolios except the Long portfolio. The decrease in the short duration premium from 9.3% to 9.0% as a result of yearly rebalancing is statistically insignificant, and the Sharpe ratio remains constant at 0.59. Therefore, we conclude that the short duration premium persists when increasing the practicality of asset management by lowering the frequency of rebalancing. Furthermore, we note that in addition to maintaining the same risk-adjusted strategy return, the transaction costs that result from Gonçalves' (2021) continuous rebalancing might be reduced.

2.2.6.3 Adjusted Volatility Managed Strategy

To validate the results presented in *2.2.3 Results of the Volatility Managed SML Strategy,* we volatility manage the SML portfolio with the adjustments of consistency and yearly rebalancing, as described in *2.3.1* and *2.3.2,* respectively. Although both adjustments result in lower SML premiums, investors could benefit from the reduced noise and the unrealized benefits of lower transaction costs. We find that there is no notable change in the results of the consistent and yearly rebalanced, volatility managed SML (see *Appendix 6*). As we increase the robustness of our SML strategy, the alphas of the volatility managed SML become less negative, but remain insignificant when regressed on the CAPM, and Fama-French three- and five plus momentum. On this basis, we conclude that there are no economic gains to volatility managing the equity duration strategy, following Moreira and Muir's (2017) approach and based on Gonçalves' (2021) duration measure.

Although volatility management did not improve the SML premium, the equity duration strategy can be used in combination with other investment strategies to maximize investors' risk-adjusted returns. In the next chapter, we explore the benefits of including the SML in a multifactor environment.

2.3 Optimizing the Multifactor Model

The findings in chapter *2.2* suggest that volatility managing the equity duration strategy, does not lead to an improvement of the original strategy. For further analysis we therefore set aside volatility management and further explore the short duration premium. In this chapter, we address a multifactor environment, where we seek to optimize investors' Sharpe ratio by combining the SML with traditional asset pricing models. The magnitude of the increase in the optimized portfolio's Sharpe ratio indicates whether the consideration of equity duration shows merit to sophisticated investors. To construct the multifactor model, we follow Markowitz' (1952) paper "Portfolio Selection" on individual securities, but instead create portfolio combinations of factors, including SML, Fama-French three (FF3) (1996) and five factors (FF5) (2015), and the momentum factor (Jegadeesh & Titman, 1993).

2.3.1 The Multifactor Model

In this section we look at a factor-based extension of the Markowitz (1952) portfolio optimization framework. According to Bjørnson and Gjerde (2017), Fama-French models (1996, 2015) have previously been used as a replacement for Markowitz' model (1952), whereas we wish to combine these two concepts. The primary purpose of creating a portfolio consisting of SML, Fama-French factors and momentum, is to check if this would beat the original models excluding SML (Fahmy, 2020). The optimal portfolio of factor weights only relies on historical data.

The mean-variance (MV) efficient portfolio selection of Markowitz (1952) is based on two concepts: investors wish to maximize returns, and investors consider returns desirable and variance undesirable (Markowitz, 1952). Incorporating additional factors in a portfolio, increases diversification, which is desired by investors given risk-aversion (Lintner, 1965). The MV framework takes into consideration the mean and the standard deviation (μ_P, σ_P) of a particular portfolio (*P)* of asset returns. Given the target rate of return of *n* assets, the investor optimized the weights distributed to each asset so that the risk-return relationship is maximized (Fahmy, 2020). We follow the same methodology but apply it to a variety of factor strategies instead of assets, including SML. Assuming all factors lie inside the mean-variance frontier, we find the optimal portfolio on the efficient frontier of risky assets (Santos, 2020).

To create the portfolio that optimizes Sharpe ratio, we first calculate the expected returns and the variance of each individual factor. The expected return of a portfolio is calculated as follows:

$$E(r_P) = \sum_{i=1}^{n} w_i \, E(r_i) \tag{6}$$

The variance of two factors (*x* and *y*) in a portfolio is:

$$\sigma_P^2 = w_x^2\sigma_x^2 + w_y^2\sigma_y^2 + 2w_x w_y \, Cov(r_x, r_y) \tag{7}$$

Expanding this to a multifactor environment we have:

$$\sigma_P^2 = \sum_{i=1}^{\infty} w_i \sigma_i^2 + \sum_i \sum_{j \neq i} w_i w_j Cov(r_i, r_j) \tag{8}$$

When generalizing equation *(6)* to more than two factors, we introduce a matrix multiplication to find the optimal weights of the different factors in the portfolio. These weights are calculated at the start of each month. The expected return is then:

$$E(r_P) = W^T R = \begin{bmatrix} w_1 & \dots & w_j \end{bmatrix} \begin{bmatrix} E(r_1) \\ \vdots \\ E(r_j) \end{bmatrix} \tag{9}$$

Where W^T is a vector of weights and *R* is the expected return vector of each individual factor. The variance of the portfolio is defined as below, where *S(W)* is the variance of the variance-covariance matrix between each factor included in the portfolio. The covariance between the same factor, is just the variance of the factor itself.

$$\sigma_P^2 = W^T S(W) = \begin{bmatrix} w_1 & \dots & w_j \end{bmatrix} \begin{bmatrix} \sigma_{11} & \cdots & \sigma_{1j} \\ \vdots & \ddots & \vdots \\ \sigma_{j1} & \cdots & \sigma_{jj} \end{bmatrix} \begin{bmatrix} w_1 \\ \vdots \\ w_j \end{bmatrix} \tag{10}$$

To optimize the MV portfolio of different combinations of factors, we maximize the Sharpe ratio of our multifactor portfolio:

$$S_p = \frac{E(r_p)}{\sigma_p} \tag{11}$$

2.3.2 Adding the Equity Duration Factor

In our multifactor model, we investigate the Sharpe ratio of different combinations of factors: Market risk-free (Mkt), small minus big (SMB), high minus low (HML), robust minus weak (RMW), conservative minus aggressive (CMA), betting on momentum (MOM) and small minus long duration (SML). As an example, the return of the seven-factor portfolio model (*8*) in *Table 11*, can be expressed as:

$$R_t = w_1 Mkt_t + w_2 SMB_t + w_3 HML_t + w_4 RMW_t + w_5 CMA_t + w_6 MOM_t + w_7 SML_t + e_t \tag{12}$$

Table 11:
Mean-variance Efficient Portfolio

The table presents the mean-variance efficient portfolios for a set of factor combinations from July 1973 to June 2019. The factors considered is the equity duration strategy (SML), Fama-French three- (FF3) (1996) *and five-factor models (FF5)* (2015)*, and the momentum factor (MOM)* (Jegadeesh & Titman, 1993)*. Panel A summarizes the optimal weights of each factor in each multifactor portfolio, where factor weights add up to one. The value weighted SML buys Short duration firms and sells Long duration firms and is created every June from 1973 to 2018 based on duration estimates by Gonçalves (2021, 3). In Panel B, we present the comparable results of Moreira and Muir's* (2017) *multifactor portfolios (1926-2015). Monthly returns (x 12) and Sharpe ratios (x $\sqrt{12}$) are annualized.*

Panel A: Mean-Variance Efficient Portfolios								
Factor weights	(1) MKT	(2) FF3	(3) FF3 MOM	(4) FF3 SML	(5) FF5	(6) FF5 MOM	(7) FF5 SML	(8) FF5 MOM SML
SML				0.39			0.12	0.11
MktRF	1.00	0.34	0.25	0.40	0.18	0.17	0.21	0.20
SMB		0.16	0.09	0.00	0.12	0.10	0.04	0.04
HML		0.49	0.39	0.21	0.00	0.00	0.00	0.00
RMW					0.29	0.24	0.25	0.21
CMA					0.41	0.38	0.37	0.35
MOM			0.27			0.10		0.10
Annual return	7.15 %	4.65 %	5.38 %	7.24 %	4.10 %	4.49 %	4.99 %	5.21 %
Sharpe ratio	0.45	0.69	0.97	**0.90**	1.14	1.27	**1.28**	**1.39**

Panel B: Portfolio results from Moreira and Muir (2017)								
Sharpe ratio	0.42	0.52	0.98		1.19	1.34		

Table 11 reports the optimal weights of each factor for a set of investment strategy combinations and their corresponding performance. The number of different factors in a portfolio, reflects investors' ability to gather stock information: More sophisticated investors can invest in many factors, and less sophisticated investor can only invest in one or a few factors (Moreira & Muir, 2017). In *Table 11, Panel A*, the weights are optimized to generate the maximum Sharpe ratio for each multifactor portfolio (column 1-8). As adding one more investment strategy will always deliver the same, or a higher Sharpe ratio than the original portfolio selection, we are interested in the relative increase in the Sharpe ratio when adding SML, as compared to adding another strategy.

Model (1) solves the Markowitz optimization with a 100% weight in the market portfolio, this being the only factor available. In model (2), we find optimal weights for FF3 and document an increased Sharpe ratio[17] from 0.45 to 0.69, proving that there are gains from having more than just the market portfolio available. In model (3), we add momentum and observe another increase in the Sharpe ratio from 0.69 to 0.97, and a return of 5.55%, while the weights of all FF3 factors decrease. Alternatively, when adding SML to FF3 (4) we increase Sharpe ratio from 0.69 to 0.90 and document a return of 7.24%. The Sharpe ratio is somewhat lower than when FF3 is combined with momentum, while returns are 1.86 percentage points higher. Mean-variance investors would prefer adding momentum rather than SML to the FF3 model due to a lower risk-return ratio. However, risk seeking investors could achieve higher utility by adding the SML strategy, instead of the momentum factor.

Model (5) combines FF5 factors, which returns a Sharpe ratio of 1.14. When combining FF5 with SML in model (7), we get an increased Sharpe ratio of 1.28, which is slightly higher than when combining FF5 with momentum (Sharpe ratio of 1.27). The fact that SML contributes to a higher Sharpe ratio than the renowned momentum strategy, underlines the merits of the SML strategy. Model (8), which combines all available factors, FF5, the momentum strategy and SML, naturally generates the highest documented Sharpe ratio of 1.39. We perform the same analysis when including the volatility managed SML from section *2.2* instead of the original SML (see *Appendix 7*). As expected, adding SML* to FF3 and FF5 does not outperform incorporating SML or momentum.

When expanding Markowitz' (1952) MV efficient portfolio theory to combinations of factors, we discover improved risk-return relationships after adding the short duration premium factor. However, not every investor will be sophisticated enough to have all the seven factors available. Less sophisticated MV investor will perhaps only be capable of investing in FF3 and one other factor, and should then include momentum instead of SML to maximize their Sharpe ratio. The opposite is true for more sophisticated MV investors, that have the FF5 available, as they should incorporate SML before momentum. Combining all seven factors return the highest Sharpe ratio of 1.39, which therefore becomes the desired portfolio for a

[17] Moreira and Muir (2017) state that Sharpe ratios might be overstated in a multifactor portfolio as weights are created for a sample.

mean-variance investor. The relatively high increase in Sharpe ratios when adding the SML to Markowitz' portfolio optimization models, highlights the merits of the equity duration strategy.

3 Conclusion

In recent literature, the equity duration strategy has proven to yield a significant short duration premium over classical factor models. This thesis contributes to the research agenda by volatility managing the equity duration strategy, and by including the equity duration strategy in the multifactor model. We explore whether managing the volatility of the short duration premium yields higher risk-adjusted returns, as it has proven to do for several well-established investment strategies (Moreira & Muir, 2017). To ensure the validity of the short duration portfolio used for volatility management, we replicate portfolios constructed on equity duration estimates by Gonçalves (2021, 3). Our results show a clear downward-sloping equity term premium. We find a 9.3% annualized short duration premium in our Short- minus Long (SML) equity duration portfolio, with statistically insignificant differences to Gonçalves' (2021) results. Replication results confirm the validity of the SML strategy we use for volatility management and the multifactor model.

To manage the volatility of the SML duration strategy, we follow Moreira and Muir's (2017) methodology of increasing exposure when strategy volatility is low and decreasing exposure when volatility is high. Our hypothesis, that volatility managing the short duration premium yields increased risk-adjusted returns, is rejected. We find a statistically significant decrease of 4.2% annualized returns for the value weighted SML strategy when managing its volatility. Regressing the volatility managed SML on CAPM and the original SML, we find a negative alpha of 2.8%, statistically significant at the 10% level. The original SML strategy features a positive relationship between volatility and returns. Therefore, volatility managing the equity duration strategy, generally result in increasing risk-taking in periods of low return and reducing risk-taking in periods of high return, contrary to the rationale of volatility management. Hence, by volatility managing short duration premium, we eliminate the significant right skew of 0.64 of the original strategy. We argue that the decrease in risk-adjusted returns is not a contradiction to the validity of the volatility management strategy, but rather a mismatch between the underlying characteristics of the short duration premium and the functionality of volatility management.

To understand how the cyclicality of SML impacts the effectiveness of its volatility management, we analyze the best and worst performing months of the SML strategy and the market. Inspecting the SML strategy's 10% most extreme positive and negative monthly returns, the volatility managed SML yields 3.9% lower annualized returns in high performance months, while improvements in returns in low performance months is statistically insignificant. Further supporting the dysfunctionality of volatility managing SML, the volatility managed portfolio yields 2.3% lower annualized returns in the market's low performance months, while improvements in returns in the market's high performance months is statistically insignificant. We argue that one reason for the poor performance of the volatility managed SML is rooted in the cyclicality of the SML's volatility and return.

To validate our results, we confirm the effectiveness of Moreira and Muir's (2017) variance prediction by finding a statistically insignificant difference between predicted and realized monthly SML variance. Further, we validate our findings by volatility managing an adjusted SML strategy. This strategy only buys and sells firms that are consistently allocated to the short and long portfolios in the two previous years. Additionally, we deviate from Gonçalves' (2021) monthly rebalancing, by rebalancing our adjusted portfolio yearly. In our adjusted portfolio, we diminish potential transaction costs, while risk-adjusted returns remain unchanged. In regressing the adjusted volatility managed SML on the original SML and CAPM, the alpha becomes less negative than for the original volatility managed SML.

We contribute further to the knowledge of the short duration premium by combining it with traditional asset pricing models in a multifactor environment, based on Markowitz' (1952) portfolio optimization model. The merit of the short duration premium is confirmed through significant increases in Sharpe ratios when adding the equity duration strategy to optimized portfolios of established investment strategies (Fama-French three- and five factors). We find that multifactor models incorporating the equity duration strategy could even outperform multifactor models including the renowned momentum strategy. This finding underscores the potential gains of considering assets' equity durations for sophisticated investors.

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5 Appendix

Appendix 1: Equity Duration Measure (Gonçalves, 2021).

Equity duration as constructed by Gonçalves (2021), is determined by whether the cash flows of a stock is concentrated in the close or distant future, building on the concept of bond duration by Macaulay (1938). Gonçalves creates a measure for equity duration under the assumption that the logarithmic values for profitability and growth develop linearly. *j* represents a firm index and *t* a time index[18].

Duration can be explained as the average maturity (in years) of cash flows coming from an investment and can be defined as:

$$Dur = \sum_{h=1}^{\infty} w_{j,t}^{(h)} * h \tag{13}$$

The weight, $w_{j,t}^{(h)}$ is the fraction of the invested value, *V*, in a firm of which is due to the cash flow, *CF*, that matures in *h* years at a discount rate of *dr*, and can be defined as:

$$w_{j,t}^{(h)} = \frac{\left(\mathbb{E}_t\left[CF_{j,t+h}\right] * e^{-h*dr_{j,t}}\right)}{V_{j,t}} \tag{14}$$

$Dur_{j,t}$ is the weighted average of cash flow maturities, and the weights are depending on how important the cash flow is to the investment value. Hence, the sum off all weights is equal to 1 ($\sum_{h=1}^{\infty} w_{j,t}^{(h)} = 1$). If $Dur_{j,t}$ is low, this tells us that the investment value matures in short-term cash flows, and if $Dur_{j,t}$ is high, this tells us that the investment value matures in long-term cash flows.

Equity duration is however more complex to estimate than bond duration. It is challenging to estimate the value of future cash flows, because in contrast to coupon payments and face values for bonds, they are unknown at time *t.* Additionally, bond yields, $dr_{j,t}$ are observable at time *t*. To define equity duration, Gonçalves use companies' payout as a proxy for cash flows to stockholders, which means that the investment value, *V*, is a company's market equity ($ME_{j,t}$). Payouts ($PO_{j,t+h}$) is defined as dividends + repurchases – issuance. The weights are defined as an equation of PO and ME:

$$w_{j,t}^{(h)} = \frac{\left(\mathbb{E}_t\left[CF_{j,t+h}\right] * e^{-h*dr_{j,t}}\right)}{ME_{j,t}} \tag{15}$$

The discount rate $dr_{j,t}$, is the rate that satisfies that the sum of all weights is equal to 1, hence the discount rate is the rate that solves the valuation equation:

[18] An overview of abbreviations can be found in Appendix 2: Abbreviations, Panel A.

$$ME_{j,t} = \sum_{h=1}^{\infty} \mathbb{E}_t\left[PO_{j,t+h}\right] * e^{-h*dr_{j,t}} \tag{16}$$

Equations (13) and (16) together express the full definition of equity duration.

Estimating $\mathbb{E}_t\left[PO_{j,t+h}\right]$ is the principal challenge when estimating equity durations. To do so, Gonçalves (2021) follows Vuolteenaho (2002) and Campbell et al. (2009), and introduces a state vector, $s_{j,t}$ which is a vector of firm level characteristics that follow a first order vector autoregressive (VAR) system[19]. $Dur_{j,t}$ is an implicit function of the VAR parameter estimates and $s_{j,t}$.

To estimate $s_{j,t}$, Gonçalves (2021) use 12 state variables than can be split into four categories:

I. Valuation measures:
   - Book to market $bm_{j,t} = \log\left(\frac{BE_{j,t}}{ME_{j,t}}\right)$
   - Payout yield $POy_{j,t} = \log\left(1 + \frac{PO_{j,t}}{ME_{j,t}}\right)$
   - Sales yield $Yy_{j,t} = \log\left(\frac{Y_{j,t}}{ME_{j,t}}\right)$

II. Growth measures:
   - Book equity growth: $BEg_{j,t} = \log\left(\frac{BE_{j,t}}{BE_{j,t-1}}\right)$
   - Asset growth: $Ag_{j,t} = \log\left(\frac{A_{j,t}}{A_{j,t-1}}\right)$
   - Sales growth: $Yg_{j,t} = \log\left(\frac{Y_{j,t}}{Y_{j,t-1}}\right)$

III. Profitability measures:
   - Clean surplus profitability: $CSprof_{j,t} = \log\left(1 + \frac{CSE_{j,t}}{BE_{j,t-1}}\right)$
   - Return on equity: $Roe_{j,t} = \log\left(1 + \frac{E_{j,t}}{0.5BE_{j,t}+0.5BE_{j,t-1}}\right)$
   - Gross profitability: $Gprof_{j,t} = \log\left(1 + \frac{GP_{j,t}}{0.5A_{j,t}+0.5A_{j,t-1}}\right)$

IV. Capital structure measures:
   - Market leverage: $Mlev_{j,t} = \frac{B_{j,t}}{ME_{j,t}+B_{j,t}}$
   - Book leverage: $Blev_{j,t} = \frac{B_{j,t}}{A_{j,t}}$
   - Cash holding: $Cash_{j,t} = \frac{C_{j,t}}{A_{j,t}}$

To construct these variables, Gonçalves (2021) uses stock return data from CRSP and accounting data from Compustat.

[19] See Gonçalves (2021) for technical derivations.

Appendix 2:
Abbreviations

The table provides an overview of abbreviations used in this thesis. In Panel A, we explain abbreviations used to explain the creation of the equity duration measure. In Panel B, we explain abbreviations used in regressions. These lists are not exhaustive for all abbreviation in the thesis.

Panel A: Equity Duration Measure Input			
Abbreviation	Meaning	Comment	Source
Dur	Duration as defined by Gonçalves	Based on DSS Dur (Dechow et al.	Gonçalves (2021)
DSS Dur	Duration as defined by Dechow et al.		Dechow et al. (2004)
V	Invested value		
ME	Market equity		CRSP
BE	Book equity	Following Davis, Fama, and	Compustat
PO	Net payout ratio	Following Boudoukh et al. (2007)	Compustat
Y	Total revenue		Compustat
A	Total assets		Compustat
CSE	Clean surplus earnings		Compustat
E	Earnings before extraordinary items		Compustat
GP	Gross profit	Following Novy-Marx (2013)	Compustat
B	Total book debt		Compustat
C	Cash and short-term investments		Compustat

Panel B: Regression Input			
SML	Short minus long duration		
SML*	Volatility managed SML		
MktRF	Market risk-free		Kenneth R. French's Data Library
SMB	Small minus big		Kenneth R. French's Data Library
HML	High minus low		Kenneth R. French's Data Library
CMA	Conservative minus aggressive		Kenneth R. French's Data Library
RMW	Robust minus weak		Kenneth R. French's Data Library
MOM	Momentum		Kenneth R. French's Data Library
FF3	Fama-French three factors		Kenneth R. French's Data Library
FF5	Fama-French five factors		Kenneth R. French's Data Library

Appendix 3:
Firm Characteristics in Duration Portfolios

The table reports the weighted average duration estimate and weighted average firm characteristics for firms within each duration portfolio, as found in our data sample and that of Gonçalves (2021)*, based on duration estimates from Gonçalves (2021, 3). Our sample runs from July 1973 to June 2019. In addition to duration and size, the 12 variables presented are the inputs of the VAR state vector determining each firm's duration estimate. Following Gonçalves, the weighted averages are calculated based on firms' market equity in June of year t-1, then we find the time averages for each characteristic within each portfolio. Numbers in bold illustrates statistically significant coefficients at the 5% level.*

Panel A: Firm Characteristics in Duration Portfolios

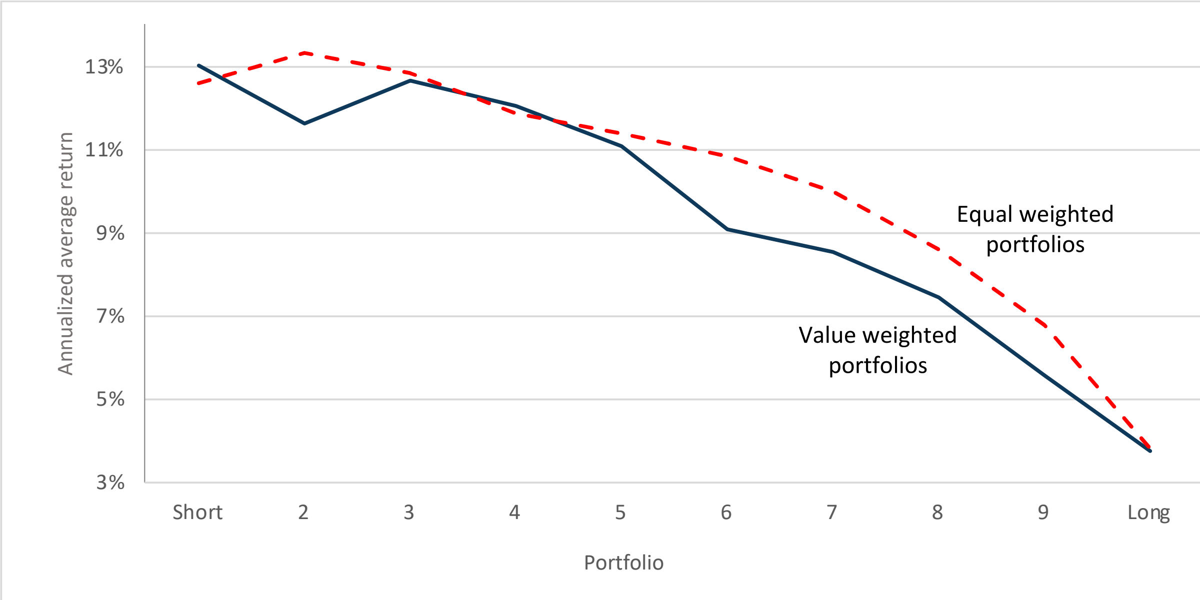
Duration			Valuation			Growth			Profitability			Capital Structure		
Portfolio	Duration	Size	BM	PO/ME	Y/ME	Beg	Ag	Yg	Csprof	Roe	Gprof	Mlev	Blev	Cash
1	17.28	7.1	1.22	.05	4.18	.01	.06	.03	.08	.05	.35	.27	.18	.11
2	25.07	7.8	.88	.05	2.71	.05	.09	.05	.14	.10	.36	.23	.20	.11
3	30.31	8.2	.75	.05	2.02	.08	.11	.08	.18	.12	.35	.20	.19	.11
4	34.81	8.7	.67	.05	1.74	.05	.09	.06	.16	.13	.34	.20	.20	.11
5	38.92	9.1	.61	.05	1.46	.07	.09	.08	.18	.14	.33	.18	.20	.12
6	43.36	9.3	.55	.05	1.23	.09	.11	.09	.21	.15	.33	.18	.21	.11
7	48.56	9.4	.51	.04	1.12	.10	.11	.10	.21	.16	.32	.18	.22	.11
8	55.30	9.2	.50	.04	1.03	.10	.11	.10	.21	.14	.29	.19	.23	.10
9	67.63	8.8	.43	.03	1.05	.13	.13	.14	.21	.12	.26	.21	.25	.10
10	114.87	8.7	.38	.03	1.29	.14	.14	.16	.24	.10	.19	.28	.30	.11
SML	**-97.6**	**-1.7**	**.84**	**.02**	**2.88**	**-.13**	**-.09**	**-.13**	**-.16**	**-.04**	**.16**	-.01	**-.12**	.00
(t_{SML})	*(-15.42)*	*(-1.16)*	*(7.68)*	*(6.40)*	*(6.18)*	*(-7.00)*	*(-5.26)*	*(-9.64)*	*(-8.31)*	*(-3.90)*	*(5.00)*	*(-0.23)*	*(-6.37)*	*(-0.55)*

Panel B: Firm Characteristics in Gonçalves (2021)

Duration			Valuation			Growth			Profitability			Capital Structure		
Portfolio	Duration	Size	BM	PO/ME	Y/ME	Beg	Ag	Yg	Csprof	Roe	Gprof	Mlev	Blev	Cash
1	16.5	7.7	1.42	.05	3.98	.02	.00	.01	.07	.10	.38	.29	.17	.11
2	24.7	8.4	.95	.04	2.53	.04	.03	.03	.11	.13	.38	.24	.18	.11
3	29.9	8.8	.77	.04	1.89	.05	.05	.05	.13	.14	.38	.21	.19	.12
4	34.4	9.3	.66	.04	1.58	.05	.04	.04	.14	.15	.37	.20	.19	.12
5	38.5	9.7	.58	.04	1.32	.05	.05	.05	.14	.15	.35	.18	.20	.12
6	42.9	9.9	.50	.04	1.06	.06	.07	.06	.16	.16	.34	.18	.21	.12
7	48.1	10.0	.44	.03	.91	.06	.07	.07	.15	.16	.34	.18	.22	.11
8	54.8	9.9	.41	.02	.77	.06	.08	.07	.14	.16	.31	.19	.22	.11
9	66.9	9.5	.35	.01	.71	.11	.13	.11	.15	.14	.28	.21	.26	.11
10	105.0	9.4	.29	.00	.75	.10	.17	.13	.06	.13	.22	.29	.31	.12
SML	**-88.4**	**-1.7**	**1.12**	**.04**	**3.24**	**-.08**	**-.17**	**-.11**	.01	**.13**	**.16**	.00	**-0.14**	.00
(t_{SML})	*(-14.38)*	*(-6.06)*	*(6.19)*	*(8.53)*	*(5.76)*	*(-2.76)*	*(-8.03)*	*(-7.58)*	*(0.35)*	*(3.66)*	*(3.64)*	*(0.04)*	*(-5.67)*	*(-0.32)*

Appendix 4:
Downward-sloping Term Structure of Equity

The figure illustrates falling annualized average value- and equal weighted portfolio returns as one moves from a Short duration portfolio to a Long duration portfolio. The SML strategy buys Short duration firms and sells Long duration firms daily from July 1973 to 2019. The value weighted portfolio is formed every June of year t-1 (year t starting in July), while the equal weighted portfolio is formed at the end of every month. Microcaps, defined as firms with market equities below the 20% NYSE breakpoint are excluded from equal weighted portfolios.



Appendix 5:
Consistent Portfolio Performance – Equal Weighted Portfolios

The table shows the excess return of equal weighted duration portfolios and the short duration premium for our consistent and original data samples. The requirement of the Consistent Data Sample is that a firm at time t must have been allocated to the same duration portfolio (pX), or one portfolio above (pX+1), or one portfolio below (pX-1), in the two previous years (t-1 and t-2). As a consequence of this restriction, our sample is limited to observations between July 1975 and June 2019. Panel A shows annualized average monthly returns (x 12) and Sharpe ratios (x $\sqrt{12}$). In Panel A, t_{stat} reported in parentheses confirm whether there is a statistical difference between the returns of the Short and the Long duration portfolios. Panel B reports the difference in annualized average premiums of the original and consistent SML. t_{stat} reported in parentheses confirm whether there is a statistical difference between the short duration premiums of the consistent and original portfolios.

Panel A: Consistent Portfolio Performance

Duration decile	Consistent Data Sample		Duration decile	Our Original Portfolios	
	Excess return	Sharpe ratio		Excess return	Sharpe ratio
Short	13.0 %	0.71	Short	12.3 %	0.64
2	13.2 %	0.76	2	13.3 %	0.73
3	**13.6 %**	**0.78**	3	12.8 %	0.70
4	12.8 %	0.74	4	12.1 %	0.67
5	10.7 %	0.64	5	11.3 %	0.63
6	9.9 %	0.58	6	11.0 %	0.60
7	9.5 %	0.54	7	10.0 %	0.52
8	8.5 %	0.45	8	8.7 %	0.44
9	6.6 %	0.32	9	7.0 %	0.32
Long	4.2 %	0.18	Long	4.1 %	0.16
SML	8.8 %	0.60	SML	8.2 %	0.59
(t_{SML})	*(4.15)*		*(t_{SML})*	*(3.93)*	

Panel B: Testing the Difference

			Difference	t-value
$SML_{Consistent}$	-	$SML_{Original}$	0.6 %	(0.52)

Appendix 6:
Regressions of Consistent and Yearly Rebalanced SML*

The table shows the excess return and factor loadings of the value weighted volatility managed SML strategy, SML. The SML strategy buys Short duration firms and sells Long duration firms daily from July 1973 to 2019, and is formed every June of year t-1 (year t starting in July). Following Moreira and Muir (2017), the volatility managed SML uses the realized variance of the previous month to scale its monthly exposure to SML. The requirement of the Consistent Data Sample is that a firm at time t must have been allocated to the same duration portfolio (pX), or one portfolio above (pX+1), or one portfolio below (pX-1), in the two previous years (t-1 and t-2). As a consequence of this restriction, our sample is limited to observations between July 1975 and June 2019. Each column represents a regression of SML* on different factors. We include monthly returns of explanatory variables: the market (MktRF), size (SMB), book-to-market (HML), profitability (RMW), investments (CMA), momentum (MOM) and duration (SML). The first five factors are factors from Fama-French (1996, 2015) and momentum is from Jegadeesh & Titman (1993). Excess return (MktRF) is market return minus the U.S. monthly T-bill rate. Alphas are annualized (x 12) and reported in percentages. P-values are in brackets and stars indicate the significance level of the coefficients: *p < 0.10, ** p < 0.05, *** p < 0.01.*

	Consistent Yearly Rebalanced				Original Value Weighted Portfolio		
SML*	CAPM SML	FF3 SML	FF5 MOM SML	SML*	CAPM SML	FF3 SML	FF5 MOM SML
SML	0.81***	0.82***	0.84***	SML	0.76***	0.77***	0.78***
	[0.00]	*[0.00]*	*[0.00]*		*[0.00]*	*[0.00]*	*[0.00]*
MktRF	0.08***	0.05*	0.03	MktRF	0.10***	0.08**	0.05
	[0.00]	*[0.08]*	*[0.28]*		*[0.00]*	*[0.01]*	*[0.15]*
SMB		0.09**	0.05	SMB		0.05	0.03
		[0.03]	*[0.26]*			*[0.25]*	*[0.59]*
HML		-0.11**	-0.01	HML		-0.09*	0.02
		[0.02]	*[0.82]*			*[0.06]*	*[0.79]*
RMW			-0.14**	RMW			-0.11*
			[0.02]				*[0.10]*
CMA			-0.17*	CMA			-0.25***
			[0.06]				*[0.01]*
MOM			0.04	MOM			0.01
			[0.15]				*[0.86]*
Alpha	-1.69	-1.41	-0.79	Alpha	-2.78*	-2.57	-1.60
	[0.25]	*[0.33]*	*[0.60]*		*[0.08]*	*[0.10]*	*[0.32]*

Appendix 7:
Mean-variance Efficient Portfolios – Volatility Managed SML

The table presents the mean-variance efficient portfolios for a set of factor combinations from July 1973 to June 2019. The factors considered is the volatility managed equity duration strategy (SML), Fama-French three- (FF3)* (1996) *and five-factor models (FF5)* (2015)*, and the momentum factor (MOM)* (Jegadeesh & Titman, 1993).*The value weighted SML strategy buys Short duration firms and sells Long duration firms daily from July 1973 to 2019, and is formed every June of year t-1 (year t starting in July). Following Moreira and Muir (2017), the volatility managed SML uses the realized variance of the previous month to scale its monthly exposure to SML. The table summarizes the optimal weights of each factor in each multifactor portfolios, where factor weights sum up to one. The table shows annualized average monthly returns (x 12) and Sharpe ratios (x* $\sqrt{12}$*).*

Factor weights	(1) MKT	(2) FF3	(3) FF3 MOM	(4) FF3 SML*	(5) FF5	(6) FF5 MOM	(7) FF5 SML*	(8) FF5 MOM SML*
SML				0.16			0.06	0.05
MktRF	1.00	0.34	0.25	0.34	0.18	0.17	0.18	0.18
SMB		0.16	0.09	0.09	0.12	0.10	0.09	0.08
HML		0.49	0.39	0.41	0.00	0.00	0.00	0.00
RMW					0.29	0.24	0.28	0.23
CMA					0.41	0.38	0.39	0.36
MOM			0.27			0.10		0.10
Annual return	7.15 %	4.65 %	5.38 %	4.97 %	4.10 %	4.49 %	4.22 %	4.58 %
Sharpe ratio	0.45	0.69	0.97	**0.73**	1.14	1.27	**1.18**	**1.30**