



Volatility-Managed Portfolios and Sentiment: Evidence from across the globe

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Dissertation written under the supervision of professor Pedro
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Dissertation submitted in partial fulfilment of requirements for the
MSc in Finance, at the Universidade Católica Portuguesa, April 3rd,
2024.

Abstract

Volatility-Managed Portfolios (VMPs) provide economic gains for mean-variance investors for several factors. Recent literature highlights that the market factor VMP has a performance that is robust to transaction costs and limits to arbitrage and its abnormal returns are concentrated in high sentiment periods. This paper delves into the relationship between the performance of volatility-managed market factors and investor sentiment globally and tests whether its performance is concentrated in high sentiment times.

By employing an inverse volatility strategy, this research analyses the performance of VMPs against its unmanaged market factors across six countries between 1986 to 2015, integrating sentiment indicators such as the Baker and Wurgler Index, and local sentiment indexes like the Consumer Confidence Index and Economic Policy Uncertainty. This paper shows alphas and Sharpe ratios for the entire sample period and across high and low sentiment periods as well as for high and low volatility times. Findings show that generally VMPs do not significantly surpass unmanaged market factors in risk-adjusted returns terms, with its performance relatively influenced by investor sentiment. More specifically, using BW as sentiment index the US VMPs' exhibit concentrated alpha in high-sentiment times, resonating with established sentiment theories. In contrast, data from Germany and France hint at stronger VMPs' abnormal returns concentration during low sentiment periods. Additionally, it is also demonstrated that different sentiment proxies lead to different performance distribution.

Keywords: Volatility-Managed Portfolios, Risk-Return Trade-off, Sentiment, Performance

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Resumo

Portfólios geridos por volatilidade (VMPs) proporcionam ganhos económicos para investidores de risco-retorno para vários fatores. A literatura realça que o VMP do fator de mercado, cujo desempenho é robusto a custos de transação e limites de arbitragem, tem performance concentrada em períodos de sentimento de investidor alto. Este estudo investiga a relação entre o desempenho dos fatores de mercado geridos por volatilidade e o sentimento dos investidores a nível global e testa se este desempenho está concentrado em períodos de sentimento de investidor alto. Utilizando uma estratégia de volatilidade inversa, esta análise investiga o desempenho das VMPs face aos seus fatores de mercado não geridos em seis países entre 1986 e 2015, integrando indicadores de sentimento como o índice de Baker and Wurgler e índices de sentimento locais. Este estudo apresenta alphas e Sharpe ratios para a amostra, e para cada período de sentimento e de volatilidade, denominados de alto e baixo. Os resultados demonstram que, geralmente, as VMPs não superam significativamente os fatores de mercado em termos de retornos ajustados ao risco, sendo o seu desempenho relativamente influenciado pelo sentimento dos investidores. Especificamente, utilizando o BW como índice de sentimento, as VMPs nos EUA exibem um alpha concentrado em períodos considerados de sentimento alto, de acordo com as teorias de sentimento estabelecidas. Contrariamente, os dados da Alemanha e França sugerem uma maior concentração da performance em períodos de sentimento baixo. Adicionalmente, é demonstrado que ao utilizar diferentes índices de sentimento são obtidos diferentes concentrações do desempenho dos VMPs.

Palavras-chave: Portfólios Geridos por Volatilidade, Relação Risco-Retorno, Sentimento, Performance

Título: Portfólios Geridos por Volatilidade e Sentimento: Resultados de todo o mundo

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Acknowledgements

I would like to express my gratitude to my parents and sister who have provided me with unconditional support and inspiration throughout my academic journey. They always showed me that with great determination and hard work, anything can be achieved. I owe my resilience to them.

I am equally grateful to my esteemed girlfriend, Ana Alves, for sharing the entire higher education journey with me and for her encouragement, understanding, and strength along the way.

Next, I want to extend a great thanks to Professor Pedro Barroso, whose guidance, expertise, and unwavering support have been pivotal in the successful completion of this research. His availability to discuss ideas, provide insightful feedback, and offer encouragement was crucial in steering this dissertation in the right direction.

Lastly, I wish to express my appreciation to all my friends who have been there for me and who have been essential in keeping my spirits high during my academic years.

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Abbreviations

Abbreviation	Description
BW	Baker and Wurgler Index
CAN	Canada
CCI	Consumer Confidence Index
DEU	Germany
EPU	Economic Policy Uncertainty
FRA	France
GBR	United Kingdom
IPO	Initial Public Offering
JPN	Japan
LTA	Limits to Arbitrage
MKT	Market factor
MKT^σ	Managed Market factor
OECD	Organisation for Economic Co-operation and Development
SR	Sharpe ratio
USA	United States of America
VMP	Volatility-Managed Portfolios
Δ CER	Gains in certainty-equivalent return

1. Introduction

Monthly volatility in equity markets is persistent, while it is weakly correlated with future returns. This fascinating phenomenon raises the possibility that, in contrast to what rational asset-pricing models predict, financial markets may let the price of risk to decrease as risk increases. By dynamically modifying portfolio leverage inversely with risk, Volatility-Managed Portfolios (VMPs) take advantage of this pattern and provide abnormal returns along with significant gains in investor utility.

Moreira and Muir (2017) demonstrate for several factors such as excess market return factor (MKT), momentum factor (MOM), profitability factor (RMW), return on equity factor (ROE), investment factor (CMA), and betting-against-beta factor (BAB) that VMPs, which take less (more) risk during periods of high (low) volatility, generate abnormal returns, increase Sharpe ratios, and provide utility gains for mean-variance investors. Furthermore, Barroso and Detzel (2021) show that once trading costs are considered these strategies are not useful for investors for most factors, by investigating whether transaction costs, arbitrage risk, and short-sale impediments explain the positive alphas of VMPs. They find that, even after using six cost-mitigation strategies, volatility management of asset-pricing factors, besides the market factor, generally produces zero abnormal returns and significantly reduces Sharpe ratios. Despite this, the abnormal returns of the volatility-managed market factor are robust to transaction costs and concentrated in stocks with low arbitrage risk and impediments to short selling.

Furthermore, Baker and Wurgler (2006) investigate how investor sentiment affects the cross-section of stock returns, particularly focusing on stocks with subjective valuations and limited arbitrage opportunities. They propose an investor sentiment index named Baker and Wurgler Index, BW, and find that during periods of low sentiment, subsequent returns are relatively high on certain types of stocks namely smaller stocks, high-volatility stocks, unprofitable stocks, non-dividend paying stocks, and distressed stocks, indicating an initial underpricing, which is corrected when sentiment is high. Additionally, Yu and Yuan (2011) examine the influence of investor sentiment on the market's mean-variance trade-off. They find that the stock market's expected excess return is positively related to the market's conditional variance in low-sentiment periods but unrelated to variance in high-sentiment periods. This suggests that sentiment traders undermine an otherwise positive mean-variance trade-off during high-sentiment periods.

Motivated by volatility-timing strategies and the conclusions of Barroso and Detzel (2021) on dissecting the performance of various volatility-managed portfolios this thesis examines the performance of the volatility-managed market factor for Canada, Germany, France, the United Kingdom, Japan, and the United States for the period between 1986 to 2015 and tests whether their performance is concentrated in high-sentiment periods, as the Yu and Yuan's (2011) results suggest. The data is divided between periods of high and low sentiment and high and low volatility to showcase in which there's a higher concentration of abnormal returns. Upon carefully examining the tables displayed, I verify that the performance of the managed market factor is not as satisfactory for the different markets studied as it is for the United States. Furthermore, when examining whether there's a concentration of performance in high sentiment periods, it is not clear whether there's a similar pattern to the one showcased in Barroso and Detzel (2021), in which for the US between 1986 to 2015 the performance is concentrated in high sentiment times, consistent with the sentiment theory. This conclusion might be the consequence of the poor results that the volatility-managed market factors provide along the sample period for the different markets. For instance, even with positive alphas for Germany, France, and the United Kingdom which might suggest that volatility timing improves the Sharpe ratio compared to the buy-and-hold market factor, they do not present statistically significant results which creates a limitation to conclude whether volatility timing boosts the performance for each market factor of the respective country.

The structure of the paper is organized as follows: Initially, the paper presents a literature review in Section 2 that serves to both support and challenge the empirical findings discussed later in the document. Following this, Section 3 delineates the methodology employed, detailing the construction process for Volatility-Managed Portfolios and the regression utilized to derive the abnormal returns and performance concentration in high sentiment times. Subsequently, the Section 4 elucidates on the dataset employed in all computational analyses, ensuring clarity on the data foundation for the research findings. In the section 5, the empirical results are unveiled, providing insights into the sample summary statistics, the performance of the respective volatility-managed market factors, and their behaviour across different sentiment and volatility periods. The paper culminates with a conclusion section that synthesizes the key findings, discusses their implications, and may propose avenues for future research. This concluding part aims to encapsulate the core insights derived from the study and underscore their relevance in the broader context of financial research.

2. Literature Review

2.1 Mean-Variance Trade-off

Despite extensive research, the Mean-Variance Trade-off remains the cornerstone in asset allocation and portfolio management literature. This simple concept, which conjugates risk and return, sets the ground for investors to choose investment strategies that allow them to maximize their expected utility, aligning with their individual risk tolerance and investment objectives.

The Mean-Variance Optimization Model, introduced in the seminal work Markowitz (1952) is a pivotal framework in Modern Portfolio Theory (MPT). This model fundamentally changed investment strategies by showcasing how portfolios can be optimized for the highest expected returns for a given level of risk. Moreover, it highlights the crucial balance between risk (variance) and expected returns (returns), leading to the concept of the efficient frontier which represents the set of portfolios that offer the maximum expected return for a specified level of risk.

Sharpe (1966) propose the Sharpe ratio (SR) as an outgrowth of his previous work on the Capital Asset Pricing Model, commonly referred to as CAPM. The SR is a fundamental tool in Finance to evaluate the performance of investment strategies and to compare them by adjusting their returns to the risk inherent. It divides a portfolio's excess returns by a measure of its volatility and when comparing similar portfolios an investor would prefer the one with the highest Sharpe Ratio.

These theories, among others, underscore the critical roles of diversification and risk management in aligning investment assets with goals, marking the core of asset allocation and portfolio management discussions. Moreover, they have provided essential tools and paved the way for advancements across various domains within asset allocation and portfolio management, enriching the field with diverse strategies and approaches to achieving optimized investment outcomes.

2.2 Volatility-Managed Portfolios (VMPs)

Volatility-Managed Portfolios (VMPs) dynamically adjust their leverage in response to volatility. By reducing the factor's exposure during high-volatility periods and increasing it when volatility is low, VMPs aim to manage risk and enhance returns.

Flemming et al. (2000) examines the performance of volatility-timing strategies for short-horizon investors employing mean-variance optimization across diverse asset classes including stocks, bonds, gold, and cash. Their findings underscore the tangible economic benefits of volatility timing, affirming its utility despite challenges in risk estimation and transaction costs. Building on these insights, Fleming et al. (2003) shows that using intra daily returns to estimate the conditional covariance matrix, referred to as the “realized” volatility approach, can lead to substantial gains in portfolio performance, with robustness to transaction costs, estimation risk regarding expected returns and the performance measurement horizon. Moreover, research by Marquering and Verbeek (2004) and Barroso and Santa-Clara (2015) show the efficacy of timing volatility for the S&P500 index and momentum strategies, respectively, not just in returns but also in mitigating risks associated with high volatility periods, especially for the momentum factor which is associated with the worst crashes.

Moreira and Muir (2017) emphasize that due to the to the high predictability of variance over short periods, and the minimal correlation between variance forecasts and future returns in these timeframes, VMPs are able to generate substantial risk-adjusted returns. They empirically demonstrate this conclusion for several factors such as the excess market return (MKT), momentum factor (MOM), profitability factor (RMW), return on equity factor (ROE), investment factor (CMA), and betting-against-beta factor (BAB). The authors highlight that their approach differs from other asset allocation papers that use volatility, as their results provide insights into the evolution of the aggregate risk-return trade-off.

The advantages of these portfolios include producing large alphas, increasing Sharpe ratios, and offering significant utility gains for mean-variance investors, even during recessions or market crises when they take relatively less risk as shown in Moreira and Muir (2017). They are beneficial across various asset classes, reducing the likelihood of extreme returns and mitigating left-tail risks, especially in “risk assets” like equity and credit as demonstrated in Harvey et al. (2018). However, there are notable disadvantages. For instance, volatility-managed portfolios do not systematically outperform their unmanaged counterparts in direct comparisons. Their out-of-sample performance often fails to surpass simple investments in unmanaged portfolios, primarily due to structural instability in the underlying strategies as outlined in Cederburg et al. (2020). Additionally, Liu et al. (2019) shows that these strategies can be challenging to implement effectively in real-time investment scenarios and may not consistently outperform the market after adjusting for transaction costs and other practical constraints. In summary, while volatility-managed portfolios offer substantial theoretical

benefits by adapting to changing market conditions and potentially improving risk-adjusted returns, they also face practical limitations in real-world applications, including challenges in implementation and consistency in outperforming unmanaged portfolios.

Deepening the research on VMPs, Barroso and Detzel (2021) test the hypothesis that Limits to Arbitrage (LTA) prevent the elimination of the abnormal returns of volatility-managed portfolios. They provide evidence that the abnormal returns of the VMPs described in Moreira and Muir (2017) are explained by the LTA such as transaction costs, arbitrage risk, and short-sell impediments. This conclusion is true for all the factors except one, the excess market returns. The abnormal returns of the volatility-managed market component are concentrated at times of low arbitrage risk and barriers to short selling and are resistant to transaction costs which confirms that the volatility-managed factor for the United States offers large risk-adjusted returns that are easy for investors to implement in real time.

2.3 Sentiment

The performance of VMPs is deeply influenced by a variety of factors, among which market's sentiment in the mean-variance trade-off stands out as particularly important. This significance is increasingly highlighted in recent research, pointing to sentiment as a key element in shaping the effectiveness of VMPs. This growing emphasis on sentiment marks a shift towards a more nuanced interpretation of how VMPs function and their efficacy in different market conditions.

Antoniou et al. (2013) claim that momentum gains are concentrated during times of high sentiment because irrational investors are overconfident in their high valuation and underreact to negative news. Research such as Stambaugh et al. (2012) and Stambaugh and Yuan (2017) indicates that when sentiment is high, returns on 11 anomalies are comparatively high. Moreover, Antoniou et al. (2016) affirm that there is evidence that inexperienced traders are more likely to engage during high sentiment times and that they overvalue high-beta equities.

Yu and Yuan (2011) is seminal in theorizing the impact of irrational traders on the mean-variance trade-off. It argues that such traders, who buy stocks when sentiment is high but refrain from shorting when sentiment is low, effectively dampen the mean-variance trade-off, albeit predominantly during periods of high sentiment. Empirically, they demonstrate that volatility forecasts market returns positively when sentiment is low and negatively when sentiment is high, ultimately resulting in an insignificant predictive relationship over their sample period. This finding introduces a critical sentiment dimension to the understanding of VMPs.

Furthering this line of inquiry, the sentiment theory of the mean-variance relation offers a plausible explanation for the alpha of volatility-managed portfolios. It suggests that the benefits of volatility timing in the market can be attributed to the persistence of volatility from one month to the next, which, unconditionally, does not correlate with future returns. The performance of $MKT^{\sigma 1}$ is intricately linked to the deterioration of the risk-return trade off as volatility increases. Investigating whether this deterioration predominantly occurs during high-sentiment periods provides deeper insights into sentiment's role, Barroso and Detzel (2021) empirically demonstrate that consistent with the sentiment theory, volatility management enhances the Sharpe Ratio (SR) when sentiment is high and diminishes it when sentiment is low. Their results, robust across various cost-mitigated versions of VMPs, align with Yu and Yuan's (2011) model, suggesting that unsophisticated traders underreact to volatility shocks in high-sentiment times.

Furthermore, the findings of Barroso and Detzel (2021) have important consequences for how investing recommendations based on VMP performance should be interpreted. The performance of VMPs, according to Moreira and Muir (2017), defies the traditional wisdom that follows significant market crashes, which states that investors should either hold onto their holdings or increase their risk-taking. The results shown by Barroso and Detzel, however, points to the validity of this common knowledge, particularly in times of low sentiment when there is a benefit to weathering market volatility. It's best to stray from traditional investing tactics when there are highly optimistic emotions, as these tend to draw in novice noise traders.

3. Methodology

The Volatility-Managed Portfolios are constructed following Moreira and Muir's (2017) approach, which uses the inverse of the conditional variance of the excess returns to build the managed factor (f_t^{σ}). Depending on changes of the conditional variance, this technique modifies the risk exposure to the unmanaged factor (f_t) each month. The reasoning is as follows, the exposure to the unmanaged factor decreases if the risk measure from the prior month increases, and vice versa. The formula for the managed portfolio formation can be found below, where the f_{t+1} corresponds to the buy-and-hold unmanaged factor (market excess return), the $\hat{\sigma}_t^2(f)$ is the proxy for the portfolio's conditional variance, calculated following the

¹ MKT^{σ} - Managed Market factor

formula in Equation 3, and c is a constant that allows the managed portfolio to have the same unconditional standard deviation as its unmanaged counterpart.

$$f_{t+1}^{\sigma} = \frac{c}{\hat{\sigma}_t^2(f)} f_{t+1} \quad (\text{Equation 1})$$

Moreira and Muir (2017) justify the use of this strategy from the portfolio problem of a mean-variance investor who is deciding how much to invest in a risky portfolio. Furthermore, given the empirical evidence that volatility is highly variable, persistent, and does not predict returns, it approximates the conditional risk-return trade-off by the inverse of the conditional variance. Additionally, this method does not require any parameter estimation and may be readily used in real time.

In Moreira and Muir (2017), the authors make use of the Equation 2 to calculate the Realized Variance which is the conditional variance aforementioned. In this study, it is followed a similar approach but it is used the sum of the squared demeaned returns between the average monthly returns and each day's market excess return divided by the number of trading days in each month, instead of accounting always 22 days for the Realized Variance of the previous period since the months do not have the same number of trading days.

$$\hat{\sigma}_t^2 = RV_t^2(f) = \sum_{d=1/22}^1 (f_{t+d} - \frac{\sum_{d=1/22}^1 f_{t+d}}{22})^2 \quad (\text{Equation 2})$$

Furthermore, it is conducted a time-series regression of the volatility-managed portfolios on the original Market factors as presented below, in Equation 3. The presence of a positive intercept (α) suggests that the unmanaged and the managed factors can be combined to achieve higher Sharpe ratios than using the unmanaged alone.

$$f_{t+1}^{\sigma} = \alpha + \beta f_{t+1} + \epsilon_{t+1} \quad (\text{Equation 3})$$

To estimate the difference in performance of the managed factor in periods of high and low sentiment, I conduct the Equation 4 in each country of the sample. The first Gamma (γ_1) depicts the difference that occurs in α between the returns of the managed factor when sentiment is high minus its returns when sentiment is low, where $D1$ is a dummy variable that assumes the value of 1 if the lagged sentiment is High and 0 if it is Low. The second Gamma (γ_2) is similar to the first one but controls the changes in β for the same difference in returns.

$$f_{t+1}^{\sigma} = \alpha + \gamma_1 D1 + \beta f_{t+1} + \gamma_2 D1 \times f_{t+1} + \epsilon_{t+1} \quad (\text{Equation 4})$$

4. Data

In constructing the Volatility-Managed Portfolios (VMPs) for this study, daily and monthly market excess returns were sourced from the AQR Capital Management website, encompassing data from Canada (CAN), Germany (DEU), France (FRA), the United Kingdom (GBR), Japan (JPN), and the United States (USA). This comprehensive dataset provides a robust foundation for portfolio construction, allowing for an extensive analysis of performance dynamics in diverse global markets.

The inclusion of market excess returns from January 1986 to December 2015 ensures a substantial time span for the examination of portfolio performance behaviour. This timeframe aligns with the availability of market excess returns for all selected countries, fostering consistency and comparability across regions. The deliberate selection of these dates is rooted in the necessity to align the findings in this dissertation with existing research literature on Volatility-Managed Portfolios and sentiment analysis. Another reason which provides validity for the period chosen for this study is that between 1986 and 2015, the managed market factor provided a significant alpha because, as stated in Moreira and Muir (2017), in the latter 30-year sub-sample, between January 1956 to December 1985, the low variation of volatility lead to insignificant alpha which consequently lead to a poor performance of the strategy.

In accordance with Yu and Yuan (2011), to gauge market sentiment it is used the yearly Baker and Wurgler (2006) index, orthogonalized to economic conditions, extracted from the Jeffrey Wurgler's website. Given that this index only considers US data, I use two local sentiment indexes, the Consumer Confidence Index (CCI), and the Economic Policy Uncertainty (EPU) index from the OECD website and the Policy Uncertainty website, respectively. These sentiment indicators, complementing the market excess returns, enriches the analysis by incorporating a local behavioural finance perspective which allows for a more refined understanding of the market dynamics influencing portfolio performance.

The deliberate synchronization of data retrieval periods between 1986 and 2015 facilitates a meaningful comparison of our results with seminal studies in the field, such as Moreira and Muir (2017) and Barroso and Detzel (2021). This alignment ensures that our findings are situated within the broader context of existing research, contributing to the academic discourse on Volatility-Managed Portfolios and sentiment analysis.

5. Empirical Results

5.1 Performance of Volatility-Managed Portfolios

Before the description of the performance of the Volatility-Managed Portfolios using Moreira and Muir (2017) approach to construct them, the excess market returns of each of the countries in the sample are analysed and outlined. As observed in Panel B of Table 1, each country presents different results for its mean, risk and Sharpe ratio between January 1986 and December 2015 providing different scenarios for the succeeding analysis and tests. Even though France's market excess returns have the highest average annualized returns, the MKT of the United States provides the highest Sharpe ratio of the sample, making it the most desirable buy-and-hold strategy among this data set for a risk averse investor. Conversely, the market factor in Japan exhibits the highest risk and the lowest average return among the samples, resulting in the lowest Sharpe ratio.

Table 1 – Performance Statistics of Unmanaged Market Factors

Panel A presents the summary statistics for monthly observations of the excess market returns of Canada, Germany, France, the United Kingdom, Japan, and the United States for the sample period between January 1986 and December 2015. Panel B shows the annualized average returns, standard deviation, Sharpe ratios and number of monthly observations used of the excess market returns for the sample.

Panel A: Summary Statistics of Market factors						
	CAN	DEU	FRA	GBR	JPN	USA
Mean	0.53	0.51	0.64	0.56	0.26	0.62
p25	-2.49	-2.65	-2.71	-2.29	-3.76	-2.08
Median	0.73	0.72	0.78	0.63	0.10	1.10
p75	4.04	4.11	4.22	3.80	4.05	3.67
Std	5.41	6.04	5.94	5.11	6.23	4.53
Min	-28.00	-20.79	-22.19	-22.60	-17.97	-23.11
Max	20.39	19.05	19.51	15.34	25.53	12.40
T	360	360	360	360	360	360
Panel B: Performance of Market factors						
	CAN	DEU	FRA	GBR	JPN	USA
E(R)	6.41	6.14	7.69	6.69	3.18	7.50
σ	18.76	20.92	20.56	17.71	21.59	15.69
SR	0.34	0.29	0.37	0.38	0.15	0.48
T	360	360	360	360	360	360

Table 2 represents the performance of the Volatility-Managed excess market returns compared against its buy-and-hold counterpart for each of the countries chosen, ignoring transaction costs. In accordance with Moreira and Muir (2017) the managed excess market returns (MKT^σ) of the United States provides a statistically significant positive alpha, which suggests that volatility timing can improve upon the Sharpe ratio of the unmanaged factor

(*MKT*) for the US. The table also outlines a positive intercept for Germany, France and the United Kingdom. Nevertheless, it is worth mentioning that none of these countries meet the threshold to be considered to have a statistically significant positive alpha. On the other hand, the cases of Canada and Japan do not present good results for volatility-timing given that their intercept is close to zero and negative, respectively, and in addition there's a deterioration in the Sharpe ratio for both countries.

Similarly, to Barroso and Detzel (2021), I utilize the approach in Campbell and Thompson (2008) that utilizes the gains in certainty-equivalent returns (ΔCER) to measure the economic significance of alphas (α) experienced by a mean-variance investor with a risk aversion of three from $SR(f)$ to $SR(f^\sigma)$. Correspondingly, the countries that exhibit positive alphas which are Germany, France, the United Kingdom, and the United States also have economically gains with improvements in certainty-equivalent returns of 0.87%, 0.54%, 1.29%, and 2.99%, respectively, per year. Furthermore, one can also observe the z-statistic from the Jobson and Korkie (1981) with the correction of Memmel (2003) following DeMiguel et al. (2009) significance test for the difference in Sharpe ratios, $SR(f^\sigma) - SR(f)$.

Upon carefully examining these results, one can state that compared to their Market factor only the United States seem to benefit from volatility-timing its market factor given that it has significant Sharpe ratio improvements in applying Moreira and Muir (2017) volatility-managed strategy. Although, Germany, France, and the United Kingdom show a positive intercept suggesting that there is a benefit to volatility-timing, it is not statistically significant. In addition, Canada and Japan strongly indicate that investors are better off with the buy-and-hold strategy.

Table 2 – Performance of Volatility-Managed Factors

This table presents a comprehensive analysis of volatility-managed and unmanaged factors. Each volatility-managed factor f^σ is regressed against its unmanaged counterpart using the model $f_t^\sigma = \alpha + \beta f_t + \varepsilon_t$, with the managed factor being adjusted by the inverse of the unmanaged factor's realized variance from the preceding month ($f_t^\sigma = (c/RV_{t-1}^2)f_t$). The table includes regression statistics, and the annualized Sharpe ratios for both the unmanaged ($SR(f)$) and managed $SR(f^\sigma)$ factors. Additionally, it reports the annual percentage improvement in certainty-equivalent returns (ΔCER) for a mean-variance investor with a risk aversion of three, who opts for the Sharpe ratio $SR(f^\sigma)$ over $SR(f)$. Covering the period from 1986 to 2015, the data are monthly and span six countries: Canada, Germany, France, the United Kingdom, Japan, and the United States. The table also features t-statistics in parenthesis and the z-statistic ($z(SR(f^\sigma))$) from the Jobson and Korkie (1981) test with Memmel's (2003) correction, assessing the null hypothesis that the difference between the Sharpe ratios of the managed and unmanaged factors is zero. The values are not reduced with the transaction costs.

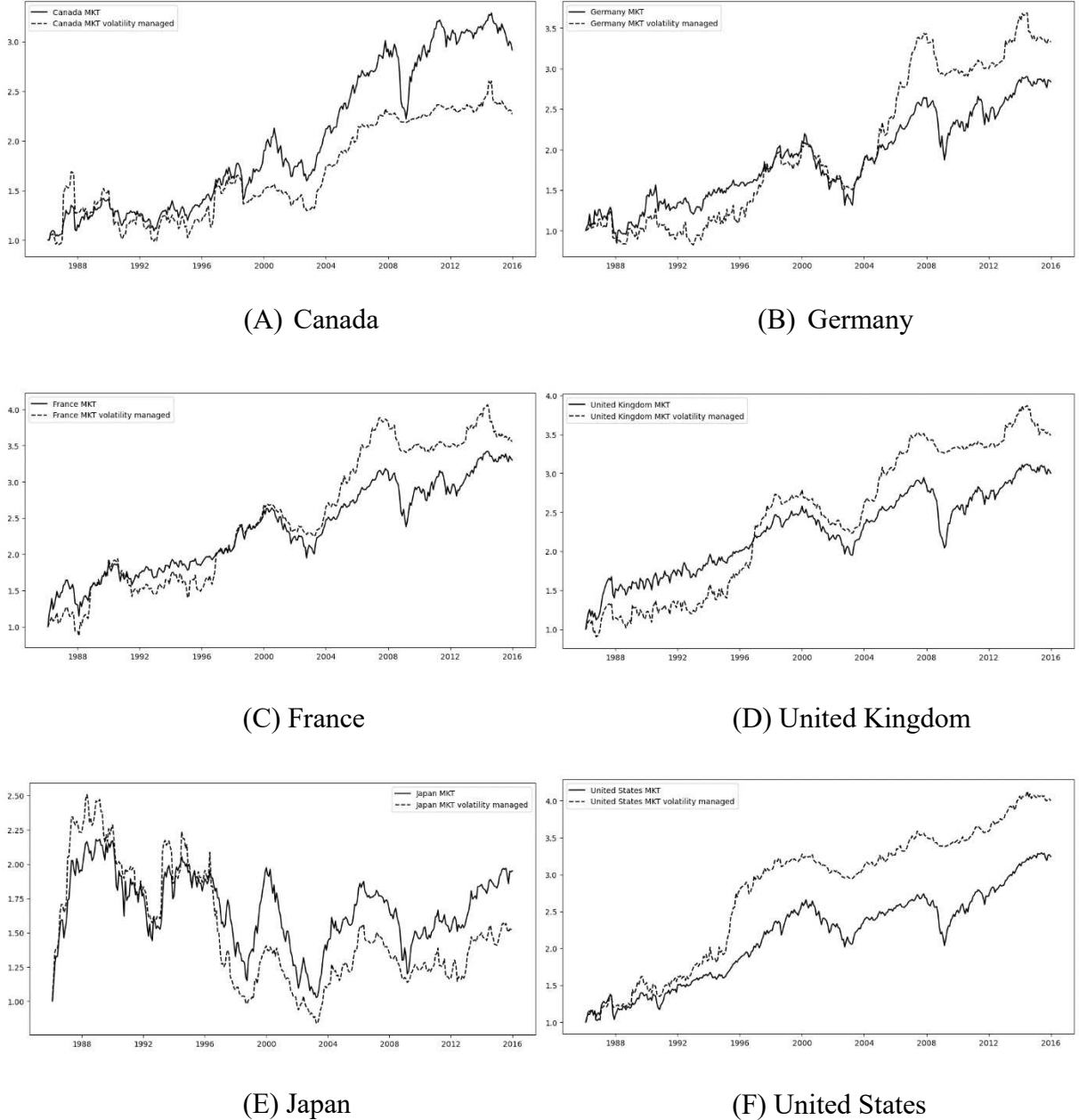
	CAN	DEU	FRA	GBR	JPN	US
α	0.03 (0.01)	3.31 (1.26)	2.77 (1.11)	3.28 (1.52)	-0.63 (-0.24)	4.88 (2.31)
β	0.66 (16.49)	0.73 (20.08)	0.75 (21.35)	0.75 (21.43)	0.76 (21.76)	0.69 (17.80)
T	359	359	359	359	359	359
R-square	0.43	0.53	0.56	0.56	0.57	0.47
$SR(f)$	0.34	0.29	0.37	0.38	0.15	0.48
ΔCER	-1.09	0.87	0.54	1.29	-0.25	2.99
$SR(f^\sigma)$	0.23	0.37	0.42	0.47	0.08	0.64
$z(SR(f^\sigma))$	-0.76	0.56	0.31	0.70	-0.51	1.10

The panels in Figure 1, in which we observe the cumulative returns for the buy-and-hold market factor and its volatility-managed counterpart, are indicative of this conclusion. One can observe that between January 1986 to December 2015 the MKT^σ outperforms the MKT in the cases of Germany, France, the United Kingdom and the United States. On the contrary, the buy-and-hold strategy outperforms its managed counterpart for the cases of Canada and Japan.

It is worth mentioning that during the Global Financial Crisis (GFC) of 2008 the VMPs allowed investors to minimize the fall in returns observed in all sample excess market returns when markets crashed, since it takes substantially less risk during recessions, as pointed out in Moreira and Muir (2017). These strategies reduce risk-taking during unfavourable periods, which contrasts with the traditional advice to either increase or maintain the level of risk-taking during such times. Conversely, periods in which volatility is low and market excess returns are positive, the VMPs amplify its returns. This pattern can be observed between 1995-1996 for the US, in the 2005-2007 period for DEU, FRA, and GBR, and between 1996 to 1997 for GBR in which the MKT^σ cumulative returns' curve steepens in relation to the corresponding MKT curve.

Figure 1 – Cumulative Returns of Market Factors and Volatility-Managed Factors

Figure 1 illustrates the cumulative returns of the market excess returns (*MKT*) and the Volatility-Managed factor for (A) Canada, (B) Germany, (C) France, the (D) United Kingdom, (E) Japan and the (F) United States for the period between January 1986 to December 2015.



5.2 The Impact of Sentiment

The primary focus of this study is to understand the relation between the performance of the volatility-managed excess market returns and the sentiment. The research on VMPs often neglects the impact of investor sentiment on the risk-return trade-off. Yu and Yuan (2011) present a theoretical model demonstrating how the behaviour of irrational investors – those who purchase stocks during periods of high sentiment but refrain from short selling when sentiment

is low – affects the mean-variance trade-off, particularly during high sentiment periods. They find that market volatility is a positive predictor of market returns in times of low sentiment, but it predicts negatively when sentiment is high, leading to a generally weak predictive relationship across the entire sample. The perceived advantage of a volatility-managed market portfolio's alpha arises because volatility, though consistent month to month, does not predict future returns. This insight supports the sentiment-based explanation for the effectiveness of market volatility timing. Barroso and Detzel (2021) identify market sentiment as a key factor that can drive mispricing, independent of the specific constraints on arbitrage for individual assets. The efficacy of the MKT^σ performance is closely tied to the weakening risk-return trade-off as volatility rises. This observation motivated the research in Barroso and Detzel (2021) to investigate whether this deterioration in the risk-return trade-off is concentrated in high-sentiment periods.

In accordance with Yu and Yuan (2011), if the Baker and Wurgler (2006) index (BW) is above or below its sample median at the end of the previous year, we categorize each month as having "high" or "low" sentiment. I apply this methodology to three different sentiment proxies: the Baker and Wurgler index (BW), the Consumer Confidence Index (CCI), and the Economic Policy Uncertainty (EPU) Index.

The BW index is a measure of an US investor sentiment which attempts to capture the propensity of investors to speculate. This indicator is constructed using several proxies for financial sentiment, including dividend premium, the closed-end fund discount, the first-day returns of IPOs, and the equity share in new issues. These proxies are then combined using principal component analysis to create a single index which represents the overall investor sentiment. In Baker, Wurgler, and Yuan (2012), the authors replicate this methodology to five other countries: Canada Germany, France, the United Kingdom, and Japan. The countries chosen for the sample are based on this paper, in which it shows that for these markets there are local BW indexes. However, the data for these local sentiment proxies are not available online.

Given that the Baker and Wurgler sentiment index is not available for the respective countries in the sample and based on evidence from previous studies such as Fisher and Statman (2003) and Schmeling (2009) in which it is used the CCI as a sentiment index, I decided to use it as a local sentiment proxy. Fisher and Statman (2003) empirically demonstrate that the CCI index has predictive power over the stock market. The CCI is an economic indicator designed to measure the degree of optimism or pessimism that consumers feel about the overall state of

the economy and their personal financial situation. The Conference Board creates and publishes this index on a monthly basis. This institution surveys about 5,000 households with the intention to gauge consumers' views on current and for the next six months business conditions, current and for the next six months employment conditions, and total family income for the next six months.

To give more credibility to this study, I decide to employ another local sentiment proxy, which is the Economic Policy Uncertainty (2016) (EPU) Index. Baker et al. (2016) find that policy uncertainty is associated with greater stock price volatility and reduced investment and employment in policy-sensitive sectors such as defence, healthcare, finance and infrastructure construction. To measure this sentiment proxy, the authors conjugate three types of underlying components: newspaper coverage of policy-related economic uncertainty, the number of federal tax codes provisions set to expire and disagreements among economic forecasters, and the dispersion between individual forecasters' predictions about future levels of the Consumer Price Index (CPI), Federal Expenditures, and State and Local Expenditures.

Table 3 displays the Sharpe ratio for MKT and MKT^σ , z-statistic from the Jobson and Korkie (1981) with the correction of Memmel (2003) following DeMiguel et al. (2009) significance test for the difference in Sharpe ratios, $SR(f^\sigma) - SR(f)$, the gains in certainty-equivalent returns similar to Campbell and Thompson (2008), the alphas and the respective t-stat for each sentiment state: High, Low and High minus Low (High-Low), which follows a Bootstrap technique² to retrieve the Sharpe ratios from both sentiment regime. Panel A expresses these results using the BW index, following Barroso and Detzel (2021), whereas Panel B and C, indicate them adopting CCI and EPU index, respectively, as the local sentiment proxies.

Sentiment theory states that volatility management increases the Sharpe ratio when sentiment is high and reduces the Sharpe ratio when sentiment is low. In accordance with Barroso and Detzel (2021), from Panel A of Table 3 we observe this fact for the United States, in which the alpha of the VMPs is positive and statistically significant for the high sentiment period and negative for the low sentiment period. A similar pattern occurs in Japan, although the relation is not statistically significant. In the cases of Canada and the United Kingdom the

² The Bootstrap technique randomly retrieves returns from the managed factor in high sentiment and low sentiment periods, and for the unmanaged market factor for each sentiment regime. Then it uses these returns to compute the respective Sharpe ratios for each regime and factor.

performance of the VMPs seems to be evenly distributed, for which the GBR's MKT^σ yields a positive alpha in both periods, but higher in high sentiment.

Conversely, FRA and DEU demonstrate an opposite behaviour. It seems that for these two countries, the performance of the volatility-managed market factor is concentrated in periods of low sentiment. In this sentiment regime the managed factor provides annually gains in certainty-equivalent returns of 1.44% and 2.49%, respectively. This pattern can be explained by the 2005 to 2007 period in which the excess market returns provide positive and consistent returns and, most importantly, because the volatility is mainly low during this time, the VMPs allow to escalate the returns that the buy-and-hold market factor already offers. Given that this scenario does not occur regularly throughout the whole sample, the positive alpha in low sentiment periods is not statistically significant and therefore results are not strong enough to contradict the findings on Barroso and Detzel (2021).

The results aforementioned, observed in Panel A of Table 3, utilize the BW index as the sentiment proxy. However, this index only takes into consideration US investor sentiment, given that the BW local indexes for these countries are not available. It is therefore employed the CCI and EPU, presented in Panels B and C, respectively.

Employing the CCI as a proxy for sentiment, as shown in Panel B, the analysis indicates that it accentuates the concentration of Germany's VMP performance predominantly during periods of low sentiment, with marginal statistical significance. This result points out that the positive mean-variance trade-off when sentiment is low could still be weak enough to allow for volatility-management to improve the factor's performance, contradicting the concentration in high sentiment times demonstrated in Barroso and Detzel (2021). Moreover, although the results are not statistically significant, Canada and Japan demonstrate a similar pattern in which the alpha is positive during low sentiment periods. Conversely, in the case of the United Kingdom, it is showcased a statistically significant positive alpha during periods of high sentiment, suggesting a concentration of performance during this period, in accordance with the sentiment theory and with the results found for the US using the BW index. For the other countries examined – France, and the United States – the performance of the managed factors appears to be more uniformly dispersed across both sentiment regimes, suggesting a less pronounced impact of sentiment fluctuations on these countries' VMPs performance.

In Panel B of Table 3, utilizing the EPU as a sentiment proxy reveals a discernible shift in the performance of MKT^σ in low sentiment regime for the United Kingdom, Japan, and the

United States, with both the United Kingdom and the United States exhibiting statistically significant abnormal returns during these periods. These results sharpen the puzzle for the performance concentration related to sentiment periods, given that research suggests that it is concentrated mainly in periods of high sentiment due to the deterioration of risk-return trade-off during high sentiment times shown in Yu and Yuan (2011).

In contrast, Canada demonstrates a concentration of alpha during high sentiment periods, while France and Germany exhibit abnormal returns that are relatively evenly distributed across sentiment times, although there is a subtle inclination towards low sentiment periods in France's data. However, this tendency is not statistically significant, suggesting that, in the context of France and Germany, sentiment variations as captured by the EPU do not markedly influence MKT^σ performance.

Ultimately, the results show that different sentiment indexes provide different conclusions for the volatility-managed market factors' performance concentration across the sample countries for the period between January 1986 to December 2015. The Consumer Confidence Index, the Economic Policy Uncertainty Index and the Baker and Wurgler Index have different properties from each other which seem relevant to capture time-variation in the risk-return trade-off. Given their differences to denote investors' sentiment, the concentration of MKT^σ 's performance for each country is not the same, as mentioned above. It is not clear that the volatility management increases the Sharpe ratio when volatility is high and reduces it when it is low. This fact, showcased in Barroso and Detzel (2021) for the US, depends on the sentiment proxy and the specific excess market return. Using BW index, the US, the GBR and JPN seem to follow this behaviour, whereas for DEU and FRA it is the opposite, contrary to what the sentiment literature proposes.

Table 3 – Performance of Market Factor and Volatility-Managed Portfolios across Different Sentiment Regimes

Following Yu and Yuan (2011) based on whether the preceding year sentiment index is above or below the 30-year sample median value, I categorize each month in the sample as High or Low sentiment, respectively. This procedure is the same for the three different sentiment proxies mentioned. In Table 3, the annualized Sharpe ratios of both factors for high and low sentiment periods are displayed, along with the z-statistic from the Jobson and Korkie (1981) with Memmel’s (2003) correction, assessing the null hypothesis that the difference between the Sharpe ratios of the managed and unmanaged factors is zero, and the improvement in certainty equivalent return realized (in percentage per year) by a mean-variance investor with risk aversion of three who holds the managed (MKT^σ) factor in opposition to the unmanaged factor (MKT), and the performance (α) from the Equation 3. The returns to calculate the High minus Low Sharpe ratios, and z statistic for the difference in the Sharpe ratio between high and low sentiment periods, are obtained via a Bootstrap technique. Panels A, B, and C present these results utilizing the Baker and Wurgler (BW) index orthogonalized to economic conditions, the Consumer Confidence Index (CCI), and the Economic Policy Uncertainty (EPU) index, respectively, as the sentiment proxy. The BW Index orthogonalized to economic conditions depicts only US investor sentiment and its categorization for each year is the same for all the sample countries. The CCI and EPU indexes are utilized as local sentiment proxies. Note that the CCI index of the US is also used for Canada given that its respective index is not available. The European EPU index is utilized as proxy for the Germany, France, and United Kingdom local sentiment proxies.

Panel A: Baker and Wurgler Index as sentiment proxy							
	Sentiment	SR(f)	SR(f^σ)	$z(\text{SR}(f^\sigma))$	ΔCER	α	$t(\alpha)$
CAN	High	0.13	0.08	-0.23	-0.20	-0.17	-0.04
	Low	0.64	0.48	-3.89	-2.98	0.01	0.01
	High-Low	-0.51	-0.41	0.18	-3.18	-0.17	-0.03
DEU	High	-0.07	-0.06	0.12	-0.04	-0.09	-0.02
	Low	0.73	0.83	0.51	2.49	5.77	1.60
	High-Low	-0.82	-0.88	-0.15	-2.53	-5.85	-1.11
FRA	High	0.08	0.00	-0.61	-0.10	-1.13	-0.32
	Low	0.75	0.81	0.97	1.44	4.67	1.33
	High-Low	-0.69	-0.79	-0.26	-1.54	-5.79	-1.17
GBR	High	0.17	0.31	0.71	1.07	3.26	1.01
	Low	0.65	0.64	0.23	-0.23	2.18	0.77
	High-Low	-0.48	-0.31	0.28	1.30	1.08	0.25
JPN	High	-0.12	-0.03	0.41	-0.22	1.54	0.35
	Low	0.47	0.24	-3.99	-2.65	-2.15	-0.76
	High-Low	-0.61	-0.27	0.61	2.43	3.69	0.71
US	High	0.19	0.57	1.74	4.76	7.87	2.23
	Low	0.95	0.74	-0.52	-5.75	-0.04	-0.02
	High-Low	-0.76	-0.19	1.09	10.51	7.91	1.88

Panel B: Consumer Confidence Index as the Sentiment Proxy							
	Sentiment	SR(f)	SR(f^σ)	$z(\text{SR}(f^\sigma))$	ΔCER	α	$t(\alpha)$
CAN	High	0.48	0.23	-0.60	-2.95	-3.10	-0.76
	Low	0.21	0.26	-4.49	0.35	1.60	0.63
	High-Low	0.28	-0.02	-0.55	-3.30	-4.70	-0.97
DEU	High	-0.04	-0.12	-0.58	0.23	-1.88	-0.55
	Low	0.72	0.86	1.05	3.50	7.55	1.86
	High-Low	-0.76	-0.97	-0.39	-3.27	-9.43	-1.78
FRA	High	0.09	0.20	0.64	0.57	2.95	0.83
	Low	0.66	0.65	-0.74	-0.07	3.48	0.98
	High-Low	-0.58	-0.45	0.24	0.64	-0.53	-0.11
GBR	High	0.03	0.38	2.05	2.35	5.59	2.12
	Low	0.68	0.55	0.07	-2.80	0.77	0.22
	High-Low	-0.68	-0.21	0.91	5.15	4.81	1.11
JPN	High	-0.09	-0.14	-0.26	0.18	-1.62	-0.41
	Low	0.43	0.35	-0.93	-1.04	0.55	0.16
	High-Low	-0.54	-0.50	0.06	1.22	-2.17	-0.42
US	High	0.42	0.60	0.93	2.94	5.14	1.61
	Low	0.55	0.71	0.60	3.36	4.89	1.78
	High-Low	-0.12	-0.11	0.02	-0.42	0.25	0.06

Panel C: Economic Policy Uncertainty as the sentiment proxy							
	Sentiment	SR(f)	SR(f^σ)	$z(\text{SR}(f^\sigma))$	ΔCER	α	$t(\alpha)$
CAN	High	0.02	0.10	0.50	0.15	1.34	0.43
	Low	0.76	0.32	-0.35	-7.84	-5.24	-1.36
	High-Low	-0.76	-0.25	0.99	7.99	6.58	1.33
DEU	High	0.53	0.58	-0.10	0.85	3.87	1.07
	Low	0.09	0.23	0.85	0.75	4.72	1.19
	High-Low	0.43	0.36	-0.17	0.10	0.16	0.03
FRA	High	0.59	0.62	-0.70	0.61	3.34	1.06
	Low	0.19	0.30	0.93	0.87	6.17	1.58
	High-Low	0.39	0.34	-0.15	-0.26	-0.15	-0.03
GBR	High	0.64	0.52	-0.97	-2.29	1.19	0.41
	Low	0.19	0.45	1.77	2.74	8.85	2.72
	High-Low	0.44	0.08	-0.73	-5.03	-4.80	-1.12
JPN	High	0.39	0.09	-2.12	-2.37	-3.54	-1.23
	Low	-0.01	0.08	0.47	0.11	-1.53	-0.35
	High-Low	0.41	0.02	-0.75	-2.48	-5.75	-1.10
US	High	0.87	0.96	0.52	2.83	3.94	1.81
	Low	0.32	0.58	1.58	3.93	6.98	1.96
	High-Low	0.55	0.38	-0.28	-1.10	-3.04	-0.73

Table 4 shows the correlation of market excess returns between the countries in the sample and justifies the similarities of the results aforementioned. For instance, the United Kingdom showcases a 75% correlation with the United States, for which both countries have statistically significant alphas during high sentiment periods. In addition, France and Germany that also share similar outcomes, have 86% correlation. Despite all this, it is curious that even

with 80% correlation between Canada and US, the findings in volatility-managed factors and sentiment are very different from each other.

Table 4 - Correlation between Market Excess Returns

Table 4 displays the correlation in percentage observed between country’s market excess returns with the other countries for the timeframe between January 1986 to December 2015.

	CAN	DEU	FRA	GBR	JPN	US
CAN	100	62	64	71	41	80
DEU	62	100	86	72	38	68
FRA	64	86	100	76	47	69
GBR	71	72	76	100	49	75
JPN	41	38	47	49	100	39
US	80	68	69	75	39	100

Table 5 demonstrates the correlation between the different sentiment indexes employed in this study. One can observe that there’s no strong correlation between the BW index with any of the other indexes. Furthermore, the EPU and CCI seem to be inversely correlated for the majority of the countries, which might explain the shift in the concentration of alpha across the sentiment regimes as observed in the United Kingdom’s case.

Table 5 - Correlation between Sentiment Indexes

Table 5 shows the correlation in percentage observed between the annual sentiment indexes used in the study between 1985 to 2014.

	BW	EPU CAN	EPU EU	EPU JPN	EPU US	CCI DEU	CCI FRA	CCI GBR	CCI JPN	CCI US
BW	100	-8	-27	-2	-18	0	21	14	-1	31
EPU CAN	-8	100	55	29	38	26	-53	-42	-34	-62
EPU EU	-27	55	100	55	29	-62	26	-53	-42	-34
EPU JPN	-2	29	55	100	55	-54	5	-71	-46	-55
EPU USA	-18	38	29	55	100	12	-40	-47	-52	-62
CCI DEU	0	26	-62	-54	12	100	-1	-17	32	1
CCI FRA	21	-53	26	5	-40	-1	100	58	21	70
CCI GBR	14	-42	-53	-71	-47	-17	58	100	2	74
CCI JPN	-1	-34	-42	-46	-52	32	21	2	100	27
CCI US	31	-62	-34	-55	-62	1	70	74	27	100

Table 6 takes a deeper dive into performance distribution since it distributes the Sharpe ratios of unmanaged and managed factor between periods of high and low sentiment, and high and low volatility. Following Barroso and Detzel (2021) each month is categorized as either “High” or “Low” volatility based on whether the realized variance (RV) from the previous

month, denoted as $RV_{t-1}^2 (MKT)$, exceeds or falls below the median value observed in the sample.

VMPs performance depends on the risk-return trade-off deteriorating when volatility arises and as aforementioned, sentiment theory suggests that high sentiment times denote a deterioration in the risk-return trade-off as stated in Yu and Yuan (2011). The main goal to deconstruct table 6 results is to combine literature on both topics and meticulously analyse the patterns.

Upon carefully examining Panel A, the Sharpe ratios of the managed factor are the highest during low sentiment and high volatility among the sample period for Canada, France, Japan and the United States in line with the sentiment theory. Additionally, the MKT^σ of Germany and the United Kingdom shows the highest Sharpe ratio in periods of low sentiment and low volatility, despite in DEU's case there's a bigger improvement from the unmanaged to managed factor during the low sentiment and high volatility period. With the exception of the GBR's case, the results are in accordance with Barroso and Detzel (2021) that demonstrate that there is an extra reward for enduring volatile times in the stock market when sentiment is low.

Panels B and C, that showcase the Sharpe ratios using the local sentiment proxies, exhibit different results. In the CCI's case, there's no clear pattern for which an investor would be better off generally. These peculiar results might indicate that each market has its own characteristics, suggesting investors to be meticulously attentive to the features of each specific market prior to formulating their investment decision, however this may just be random sample variation. Whereas for the EPU, Germany, France, the United Kingdom, and the United States have the highest $SR(f^\sigma)^3$ in periods of high sentiment and low volatility, contrary to the literature.

Conclusively, these results underline the fact that different sentiment indexes lead to different outcomes. Despite only taking into consideration US data, the BW index seems to provide results closer to previous literature. Perhaps using the local BW index could provide a better understanding of how the sentiment dynamics within the volatility-managed excess market returns' performance. Nevertheless, this indicates that Barroso and Detzel (2021) findings do not apply to every market.

³ $SR(f^\sigma)$ – Sharpe ratio of managed factor

Table 6 – Sharpe ratio of Unmanaged and Managed Factors by Sentiment and Volatility

Table 6 presents the Sharpe ratios for high and low sentiment and high and low volatility for both managed and unmanaged market factor for each country in the sample between January 1986 to December 2015. Panel A, B and C display these results for each sentiment proxy, BW index, CCI and EPU, respectively.

Panel A: Baker and Wurgler Index as the sentiment proxy

	Sentiment	Unmanaged factor		Managed factor	
		High Volatility	Low Volatility	High Volatility	Low Volatility
CAN	High	0.39	-0.21	0.47	0.03
	Low	0.75	0.51	1.04	0.39
DEU	High	-0.03	-0.14	-0.26	0.02
	Low	0.61	0.89	0.70	0.98
FRA	High	0.04	0.16	-0.27	0.16
	Low	0.68	0.82	1.09	0.83
GBR	High	0.15	0.20	0.06	0.45
	Low	0.53	0.78	0.36	0.81
JPN	High	-0.10	-0.14	-0.25	0.05
	Low	0.35	0.58	0.29	0.25
US	High	-0.01	0.70	-0.05	0.98
	Low	1.37	0.56	1.42	0.62

Panel B: Consumer Confidence Index as the sentiment proxy

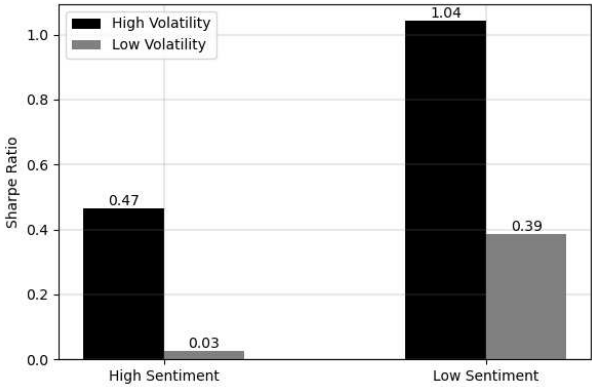
	Sentiment	Unmanaged factor		Managed factor	
		High Volatility	Low Volatility	High Volatility	Low Volatility
CAN	High	1.24	-0.06	1.49	0.10
	Low	0.14	0.41	0.19	0.34
DEU	High	0.05	-0.20	0.00	-0.21
	Low	0.52	1.01	0.40	1.07
FRA	High	-0.05	0.27	-0.07	0.34
	Low	0.57	0.83	0.60	0.77
GBR	High	-0.35	0.58	-0.34	0.74
	Low	0.96	0.40	0.83	0.56
JPN	High	-0.20	0.02	-0.30	-0.12
	Low	0.37	0.51	0.19	0.47
US	High	0.36	0.55	0.29	0.84
	Low	0.48	0.74	0.73	0.77

Panel C: Economic Policy Uncertainty as the sentiment proxy

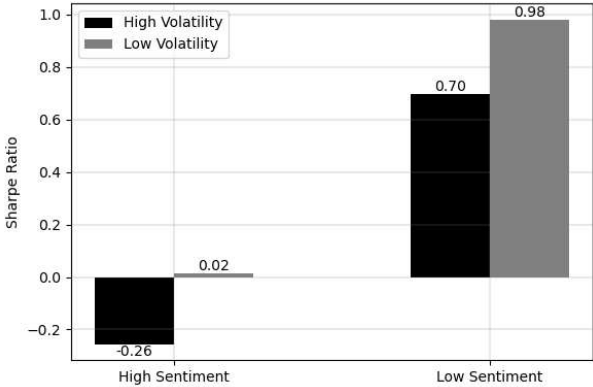
	Sentiment	Unmanaged factor		Managed factor	
		High Volatility	Low Volatility	High Volatility	Low Volatility
CAN	High	0.10	-0.14	0.00	0.15
	Low	1.38	0.28	1.74	0.17
DEU	High	0.50	0.61	0.60	0.66
	Low	-0.04	0.24	-0.22	0.40
FRA	High	0.43	1.00	0.46	0.79
	Low	0.12	0.28	0.07	0.41
GBR	High	0.56	0.79	0.31	0.68
	Low	0.07	0.30	0.14	0.61
JPN	High	0.16	0.69	0.05	-0.13
	Low	0.02	-0.04	-0.13	0.15
US	High	0.73	1.49	0.91	1.11
	Low	0.24	0.44	0.28	0.75

Figure 2 - Volatility-Managed Market Excess Returns Sharpe Ratios by Sentiment and Volatility Regime

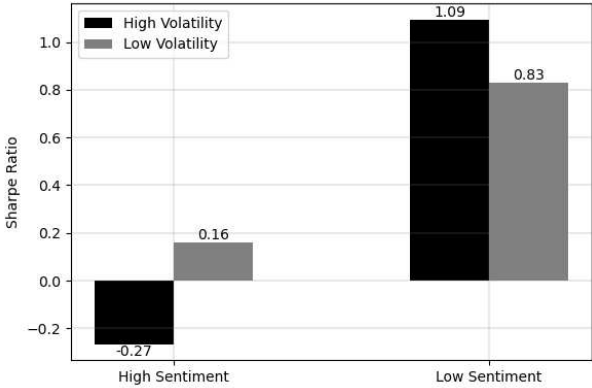
The figures illustrate the Sharpe ratio of the volatility-managed market factor for each regime of volatility and sentiment between January 1986 and December 2015. The volatility is considered as High when the prior month’s realized variance is above the sample median and expressed as Low otherwise. Panel A, B, C, D, E, and F represent the results for Canada, Germany, France, the United Kingdom, Japan, and the United States, respectively.



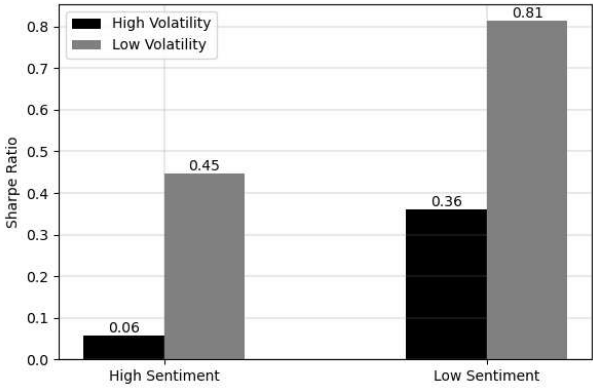
(A) Canada



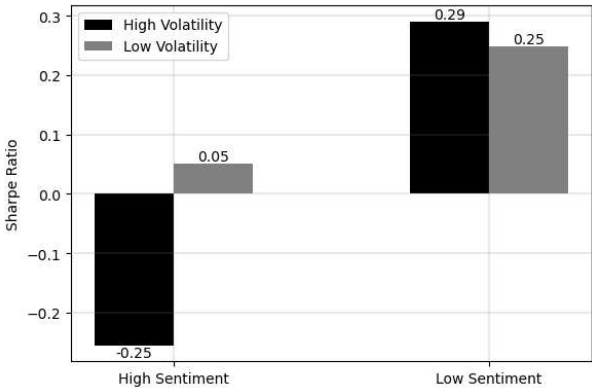
(B) Germany



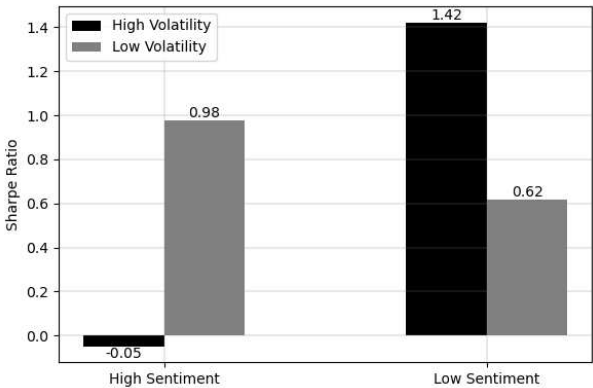
(C) France



(D) United Kingdom



(E) Japan



(F) United States

6. Conclusion and Limitations

The paper Moreira and Muir (2017) demonstrates for several factors that volatility-managed portfolios that take less (more) risk during periods of high (low) volatility generate abnormal returns, increase Sharpe ratios, and provide utility gains for mean-variance investors. The authors defy conventional wisdom by demonstrating that the strategy takes relatively less risk during recessions, which rules out typical risk-based explanations and poses a challenge to structural models of time-varying expected returns.

In Barroso and Detzel (2021), the authors empirically show that after accounting for transaction costs and other limits to arbitrage the VMPs generally produces zero abnormal returns and significantly reduced Sharpe ratios, except for the market factor. The abnormal returns of the volatility-managed market factor are robust to transaction costs and concentrated in stocks with low arbitrage risk and impediments to short selling. These findings challenge the prior literature on VMPs, by suggesting that the performance of these strategies is influenced by limits to arbitrage such as arbitrage risk, short-sale impediments, and transaction costs. Moreover, the authors find that the managed market factor only provides superior performance when sentiment is high, consistent with prior sentiment theory which states that sentiment traders underreact to volatility, suggesting that sentiment plays a role in the performance of VMPs, with higher sentiment leading to better performance.

Motivated by the latter research, the goal of this study is to examine whether performance of the MKT^σ is concentrated during high-sentiment times in countries other than the United States, namely Canada, Germany, France, Japan, and the United Kingdom, thereby, expanding the findings of previous literature to a global context.

Previous literature on deterioration of the risk-return trade-off when volatility increases use the BW index as the sentiment proxy. Using this investor sentiment measure, this thesis shows that only the United States has statistically significant concentration of abnormal returns in high sentiment times. It is not clear whether Japan and the United Kingdom also have this behaviour since they do not present statistically relevant results. Moreover, France and Germany seem to have a higher concentration of alpha in low sentiment periods, contrary to the literature. Finally, Canada's weak VMP performance is illustrated in the results, as there's no relevant positive alpha in any of the two periods.

Using CCI and EPU as the sentiment indexes it is observed a shift in the concentration of the VMPs' performance. For first one, it accentuates Germany's VMP performance

concentration in low sentiment and for the United Kingdom in high sentiment times, both with strong statistical significance. Whereas for the rest of the sample, there's a more balanced distribution in the abnormal returns between the two periods. Lastly, utilizing EPU, the US and GBR show statistically strong concentration in performance during low sentiment times while for the other markets there's a more evenly distribution.

Alongside these conclusions, it is interesting to notice that for the cases of Canada, Germany, France, and the United States there's an extra reward for enduring volatile times when sentiment is low, as stated by Barroso and Detzel (2021) for the US. One can notice that there's a clear improvement in the VMPs performance compared to its unmanaged counterpart for this specific period. Conversely, Japan and the United Kingdom show a bigger improvement in periods of low volatility and high sentiment.

Furthermore, it is important to mention that the sentiment proxies have different ways to measure the characteristics of investor sentiment and therefore have different properties, all of which are relevant to capture time-variation in the risk-return trade-off. Given this, it is clear that different investor sentiment measures do not necessarily lead to the same conclusions. Furthermore, it is not clear that the sentiment theory holds for all the sample markets, however this just might be the consequence of the not so brilliant performance of the volatility-managed market factors for the sample between January 1986 to December 2015, as only the US presents statistically significant positive abnormal returns for the whole period.

One of the primary limitations encountered in this study stems from the unavailability of local BW indexes for the sample countries. This absence necessitates the omission of these specific indexes in our analysis, which, in turn, diminishes the comparability of our results with existing literature that does utilize local BW indexes. Such a divergence is crucial as local indexes can provide nuanced insights that are more reflective of the individual market dynamics and could potentially lead to more aligned and robust findings when compared to broader, more generalized indexes. Furthermore, the employment of alternative sentiment proxies like the CCI and EPU presents an additional limitation. Although these proxies offer valuable sentiment insights, their application is not widespread within the context of sentiment analysis and VMPs. Consequently, this methodological deviation places our results somewhat apart from those in the latest studies, potentially impacts its relevance and applicability in reinforcing or challenging established academic findings within this specific field of research.

To finalize, I propose a few expansions for future research in order to increase understanding and provide a deeper look at the relationship between sentiment and volatility-managed portfolios. As it uses the same methodology for the sentiment proxy and captures the unique investor sentiment in each market, one suggestion would be to request access to the local Baker and Wurgler Index for each of the countries included in these studies. This would help to make the conclusions in Barroso and Detzel (2021) more comparable. Another one is creating volatility-managed portfolios using different formats, including six-month volatility scaling or GARCH models. Lastly, the sample of markets stated in the literature may be expanded by including other countries that have different dynamics and characteristics as the ones presented in this dissertation.

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