BI

WISEflow
Europe/Oslo(CEST)
02 Jul 2023

Handelshøyskolen BI

GRA 19703 Master Thesis

Thesis Master of Science 100% - W

Predefinert informasjon

Startdato:	09-01-2023 09:00 CET	**Termin:**	202310
Sluttdato:	03-07-2023 12:00 CEST	**Vurderingsform:**	Norsk 6-trinns skala (A-F)
Eksamensform:	T		
Flowkode:	202310||11184||IN00||W||T		
Intern sensor:	(Anonymisert)		

Deltaker

BannerId:	Eivind Myran og Torkel Nikolai Solberg

Informasjon fra deltaker

Tittel *:	Exploring the Relationship Between the Slope of the Yield Curve, Volatility, and the Profitability of Momentum Trading Strategies in US Stocks: An Empirical Analysis
Navn på veileder *:	Zhaneta Krasimirova Tancheva

Inneholder besvarelsen konfidensielt materiale?:	Nei	**Kan besvarelsen offentliggjøres?:**	Ja

Gruppe

Gruppenavn:	(Anonymisert)
Gruppenummer:	220
Andre medlemmer i gruppen:	

Master Thesis Report

at BI Norwegian Business School

Exploring the Relationship Between the Slope of the Yield Curve, Volatility, and the Profitability of Momentum Trading Strategies in US Stocks: An Empirical Analysis

By

Eivind Myran and Torkel Nikolai Solberg

Oslo, July 3, 2023

Abstract

This thesis explores the interplay between yield curve inversions, volatility and Momentum trading strategy performance in the US stock market. We test the theory that yield curve dynamics can predict fluctuations in Momentum strategy returns, with significant implications preceding and following economic downturns. Our empirical analysis uncovers patterns suggesting that the yield curve is positively correlated with momentum returns and that yield curve information gradually influences Momentum returns. Moreover, we incorporate market volatility measures to add depth to our investigation. Ultimately, this study seeks to shed light on economic forecasting through market indicators, contributing to more nuanced investment decisions and risk management.

Acknowledgments

This master's thesis signifies the culmination of our rigorous but incredibly fulfilling MSc in Finance journey at BI Norwegian Business School. The program has provided us with the essential skills and knowledge required to transition from students to professionals in the data-driven world of today.

Despite the considerable challenges brought by the COVID-19 pandemic, our lecturers adeptly adapted and maintained the quality of the course material, enabling us to learn and grow even in these trying times. We would like to express our profound gratitude to our thesis advisor, Zhaneta Krasimirova Tancheva for her invaluable feedback, guidance, and support throughout the process of writing this thesis. Her extensive knowledge was instrumental in facilitating our research and helping us navigate complex analytical problems. Lastly, we would like to extend our sincere thanks to our friends and family for their continuous support, patience, and encouragement throughout our academic journey.

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1.0 Introduction

A momentum-based trading strategy, well-known for capitalizing on existing market trends, inherently presents variable outcomes amidst fluctuating economic conditions. This strategy, which involves buying stocks exhibiting an upward return trend and selling those trending downward, has proven consistently profitable over time (Jegadeesh & Titman, 1993). However, the unique influence of macroeconomic environments on its effectiveness often remains unaddressed when evaluating momentum strategy performance.

The slope of the yield curve, a significant economic indicator often correlated with future economic conditions, constitutes one such macroeconomic environment. However, existing research has yet to fully unpack the relationship between this yield curve slope and the profitability of momentum strategies. Our thesis aims to fill this research gap, investigating the performance of momentum strategies under varying yield curve conditions in comparison to standard market conditions. Additionally, we assess the long-term performance of these strategies under the aforementioned conditions.

Momentum strategies, as suggested by past research, have retained their profitability since the 1990s, ruling out the suspicion of data snooping bias (Jegadeesh & Titman, 2001; Chordia & Shivakumar, 2002). However, the profits yielded from such strategies can be attributed to a set of lagged macroeconomic variables, suggesting that the momentum strategy payoffs vanish once stock returns adjust based on these variables (Chordia & Shivakumar, 2002). Furthermore, despite exhibiting strong average returns and Sharpe ratios, momentum strategies are susceptible to sporadic crashes, and akin to the returns of carry trades in currencies (Brunnermeier, Nagel, and Pedersen, 2008), the returns of momentum strategies are negatively skewed, leading to severe and lingering negative returns (Daniel & Moskowitz, 2016).

To scrutinize the relationship between the momentum trading strategy and the slope of the yield curve across varied economic periods, we compile historical data on US stock returns, US T-bonds, Factor Model, and risk factors spanning from July 1941 to January 2020. The wide time frame from July 1941 to January 2020 provides an expansive dataset across diverse market conditions, capturing notable economic cycles and regulatory changes (Fama & French, 1993; Fama & French, 1996). The momentum portfolios are formed by ranking stocks based on their cumulative returns from 12 months before to one month before the formation date, where the firms are then placed into one of ten decile portfolios based on this ranking, with portfolio 10 representing the winners and portfolio 1 the losers (Jegadeesh and Titman, 1993; Asness, 1994; Fama and French, 1996).

Observations on the slope of the yield curve reveals a decrease as a recession nears, a behavior that aligns with previous research suggesting that a yield curve inversion often precedes a recession. We also examine momentum returns during four distinct periods—24 to 18 months, 18 to 12, 12-6, and 6 to 0 months leading up to a recession. These periods exhibit significant market volatility and transitions in returns that reflect market uncertainty and overreaction. We analyze the momentum returns against the VIX index which shows that momentum returns are higher when VIX is elevated, suggesting that momentum strategies start to yield positive returns as market volatility increases. Splitting momentum into four portfolios ranging from the 25% percentile lowest to the 25% highest finding that returns are monotonically increasing from lowest to highest.

We further conduct a deep dive into three specific recessions: the double-dip recession in the early 1980s, the recession following the burst of the dot-com bubble in the early 2000s, and the Great Recession following the 2008 financial crisis. Our analyses considered the unique economic contexts and dynamics of these downturns to illuminate the behavior of momentum returns.

Our findings reveal a distinct correlation between momentum strategy profitability and the yield curve slope. The strategy demonstrates amplified performance, particularly momentum premium, during periods of a steep yield curve, suggesting potential for superior returns. Conversely, periods of flat or inverted yield curves sees underperformance. Interestingly, the yield curve slope also emerges as a predictor of future momentum strategy performance, providing an essential strategic tool for investors.

Our study examines the intricate relationship between momentum returns and the yield curve, specifically the predictive capabilities of lagged, simultaneous, and forward yield curve conditions. For both lagged and simultaneous yield curves, we detect a non-linear pattern of momentum returns across the four yield curve intervals, following a 1-3-2-4 sequence.

However, a paradigm shift is observed when evaluating a 2-month forward yield curve. In such instances, we identify a monotonically increasing trend, which produces the most optimal outcomes. During periods characterized by a steep yield curve, we note a significant enhancement in the performance of the momentum strategy, particularly in terms of momentum premium, thereby indicating the potential for superior returns. Here, the average momentum returns peaks at 1.0296%, aligning with the highest yield curve category.

On the other hand, under conditions of a flat or inverted yield curve, momentum strategy performance faltered, hitting a low with momentum returns of -4.5572%, corresponding to the lowest yield curve category. Our results sheds light on the predictive potency of the yield curve slope regarding future momentum strategy performance. As we traverse from the lowest to the highest yield curve category (1 to 4), momentum returns exhibit a steady upward progression, from -4.5572% to 1.0296%. This stepwise ascent underscores the yield curve's potential as an invaluable tool in shaping strategic investor decisions.

We extend our investigation to a span of 1 to 12 months, for both lagged and forward conditions. Interestingly, it we find that the predictive power of the forward yield curve diminishes beyond the 2-month mark, placing a temporal limit on its forecasting efficacy. This limitation is a crucial finding, as it outlines the temporal boundaries within which the yield curve can accurately guide momentum investment strategies.

Interestingly, the yield curve slope also emerges as a predictor of future momentum strategy performance. This insight could serve as an essential strategic tool for investors. Additionally, the impact of volatility, SMB, and yield curve factors on portfolio returns reaffirms these elements' significance in investment decision-making. However, changes in the VIX do not contribute significantly, implying that a long-short strategy based on volatility rankings might not be heavily influenced by VIX changes.

Adding to existing literature, our research spotlights the instrumental role of yield curve information for momentum investors—an area previously under-explored. This research supports the notion that financial markets are interconnected., emphasizing how economic indicators like the yield curve can significantly influence investment strategies, such as momentum investing.

The ensuing chapters of this thesis follow this structure: Chapter 2 reviews relevant literature on momentum strategies and the yield curve slope; Chapter 3 articulates our research questions and testable hypotheses; Chapters 4 and 5 detail our data collection process and adopted methodology; Chapter 6 discusses our results and offers a conclusion, drawing avenues for future research. The motivation behind this research will now be presented.

1.1 Motivation

Over the past few decades, the influence of macroeconomic indicators on various investment strategies has become an area of increasing interest and importance. Simultaneously, momentum-based trading strategies, with their ability to consistently yield profitability over time, have gained substantial traction among investors. Despite the individual popularity of these areas, there remains a surprising lack of comprehensive investigation into the interaction between the two. Hence, in the backdrop of this unexplored junction lies our motivation for the study: To understand the complex interplay between the slope of the yield curve - a crucial economic indicator, and the effectiveness of momentum-based trading strategies.

Our research questions are therefore threefold. Firstly, we aim to investigate the performance of momentum strategies under varying yield curve conditions in contrast to standard market conditions. Secondly, we seek to evaluate the predictive potential of the yield curve slope for future momentum strategy performance. Lastly, we endeavor to dissect the relationship between the Volatility Index (VIX) and momentum returns, striving to elucidate the impact of market volatility on the profitability of momentum strategies.

By addressing these questions, we hope to provide empirical insights that explain the oscillations in momentum strategy profitability in correlation with the yield curve slope and market volatility, thereby enriching our understanding of the dynamics underpinning these investment strategies.

2.0 Literature Review and Theory

The momentum trading strategy is vastly researched and proven to generate abnormal returns through several periods and across asset classes. Jegadeesh and Titman (1993) discuss the profitability of momentum trading strategies in the US stock market. Their sample includes stocks listed on The New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) between 1965 and 1989. They examine several zero-cost strategies with 4-12 months formation and holding periods finding the most profitable being ranking based on 12 months performance and a holding period of 3 months. They buy and sell the 10% percentile highest and lowest performing stocks. This strategy yields 1.31% per month with no time lag between the portfolio formation period and the holding period and yields 1.49% per month with a 1-week lag between the formation period and the holding period.

The study finds that momentum strategies continue to be profitable, despite other well-known anomalies not being observed. This is important for our research as it supports the idea that momentum trading strategies can be profitable, and concretely in the US which is where we collect our data from. As a baseline case, we examine the 12-month lookback period and 3-month holding period. There were arguments stating that the returns from these strategies either were a compensation for risk or alternatively, the product of data mining. We are using US stock data from 1941 to 2019 which gives us a wider data aspect than previous literature.

Jegadeesh and Titman (2002), continue this path adding nine extra years of research to momentum trading and find that momentum strategies continue to be profitable and by the same magnitude as earlier, suggesting that their original results were not due to data snooping bias. They find that the success of momentum strategies in their study cannot be attributed to systematic risk nor due to the delayed stock price reactions to common factors, such as market-wide events.

The study suggested that the price trends employed by momentum strategies were not a simple reflection of broad market movements or lagged responses to such movements. Importantly, their work coincided with the findings of Grundy & Martin (2001), who demonstrated that buying recent winners and shorting recent losers ensured time-varying factor exposures that corresponded with the performance of common risk factors during the ranking period. This dynamic risk exposure adjustment contributed to the stability of momentum profits across different time periods.

However, Jegadeesh and Titman (2002) noted that portions of the abnormal returns generated in the first year after portfolio formation dissipated over the following two years, a phenomenon also observable around earnings announcements of past winners and losers.

In their investigation of potential explanations, they explored the lead-lag effects, where some stocks (leaders) respond to market-wide information more quickly than others (laggers). While these effects were noticeable, they fell short of explaining the full profitability of momentum returns.

Another layer of complexity was added by the behavioral biases' theory, which posited that human cognitive biases could cause prices to deviate from their fundamental values. Consistent with the theory of delayed overreactions, they suggested that investors may underreact to new information.

Momentum strategies basing winner or loser status on stock-specific return components, as opposed to total returns, were found to be more profitable (Grundy & Martin, 2001). These findings suggested that neither industry effects nor cross-sectional differences in expected returns were the primary drivers of momentum profitability.

This led to Moskowitz & Grinblatt's (2002) investigation of industry components of stock returns, which they found to account for a significant portion of the individual stock momentum anomaly. Industry momentum strategies, which involved buying stocks from past-winning industries and selling stocks from past-losing industries, appeared highly profitable, even after controlling for size, book-to-market equity, individual stock momentum, the cross-sectional dispersion in mean returns, and potential microstructure influences.

Given the robustness of the momentum effect over time and its resistance to various conventional explanations, momentum strategy appears to be a worthy subject of deeper investigation. The authors' findings reinforce the momentum effect's validity and suggest that its underlying causes may be complex and multifaceted. Continuing research in this direction can provide valuable insights into market dynamics and investor behavior, further contributing to our understanding of momentum strategies. In our thesis, we will therefore delve deeper into momentum strategies, considering them not just as a trading strategy but as a phenomenon that provides a window into the workings of financial markets.

Building on the exploration of momentum strategies and their potential underlying causes, it is crucial to consider how these strategies perform under varying economic conditions. To extend our understanding further, we delve into the intersection of momentum strategy profitability and broader economic factors.

This juncture leads us to the insightful work of Tarun Chordia and Lakshmanan Shivakumar (2002). This study illuminates the complex interactions between momentum returns, the business cycle, and expected returns that change over time. They show that momentum profits can be explained by a set of lagged macroeconomic variables and payoffs to momentum strategies disappear once stock returns are adjusted for their predictability based on these macroeconomic variables.

By expanding our focus to include these macroeconomic factors, we can acquire a more nuanced understanding of the dynamics of momentum strategies and better equip ourselves to harness their potential.

Daniel and Moskowitz's "Momentum Crashes" (2016) stands as a key research piece, offering insights highly relevant to our study examining the interplay between momentum trading strategy and the slope of the yield curve during various economic periods. Their work dives into the particulars of momentum crashes, a term they define as periods when momentum dramatically underperforms.
Daniel and Moskowitz argue that these crashes are typically synchronized with market downturns and subsequent rebounds, marking swift reversals in the

performance of prior winning and losing stocks. This fast-paced switch in momentum can significantly impact investment strategies.

While "Momentum Crashes" does not explicitly analyze the relationship between momentum strategies and the yield curve, the insights provided are invaluable to our research. They bring to light perspectives that can significantly augment our study, enhancing our understanding of momentum returns under differing economic conditions. The study also equips us with valuable tools that can refine our methodology and provide fresh approaches to interpreting our findings. Daniel and Moskowitz's research, thus, proves to be a critical resource for our investigation into momentum strategies' performance in concerning the yield curve.

Our investigation into the relationship between momentum trading strategies and the slope of the yield curve across varying economic periods draws significant insights from a collection of foundational works. Wright's "The Yield Curve and Predicting Recessions" (2006) serves as a critical reference point, as it underscores the Treasury yield curve's role as a leading economic indicator. This study is particularly useful to our research, which focuses on the yield curve slope in different periods and its potential impacts on momentum trading strategies' profitability.

Wright's conclusion that there is more information in the yield curve's shape regarding the odds of a recession than provided by the term spread alone is vital to our study. This information is a major factor in understanding the effects of momentum trading strategies during different economic periods. Our study aims to extend Wright's analysis by linking the yield curve's shape, specifically the slope, with momentum trading profitability.

Meanwhile, Campbell and Shiller's 1991 paper, "Yield Spreads and Interest Rate Movements: A Bird's Eye View," furthers our understanding of yield spread dynamics. They find that when the yield spread is high, the long-term bond yield tends to fall, and short-term rates tend to rise. This observation could have implications for our study as it may influence the performance of momentum trading strategies.

Finally, Estrella and Mishkin's work, "The Yield Curve as a Predictor of U.S. Recessions" (1996), adds weight to the theory that the yield curve's steepness is an excellent predictor of potential future recessions. This idea, coupled with their finding that the yield curve strongly outperforms other variables at longer horizons, bolsters our research as we examine the performance of momentum trading strategies across different economic periods, often dictated by the yield curve's shape.

In short, the insights derived from these seminal works lay a strong foundation for our research into the relationship between momentum trading strategies and the yield curve. These studies also enrich our understanding of yield curve dynamics, which is crucial to our investigation and potential future applications for investors.

3.0 Research Methodology

3.1 Research Proposition

The methodology adopted in this research aims to investigate the predictive power of the yield curve on momentum returns. The analysis is structured into three primary hypotheses that seek to uncover and elucidate these intricate dynamics.

Hypothesis 1: The yield curve significantly relates to momentum returns.

Prediction 1: We predict a discernible relationship between the yield curve and momentum returns. This relationship should be visible through a comparative analysis of simultaneous, lagged, and forward values of the yield curve plotted against momentum returns. We expect momentum returns to exhibit a sensitivity to yield curve fluctuations.

Hypothesis 2: The inversion of the yield curve in periods leading to recessions, recognized as an economic forewarning, aligns with a decline in momentum returns following these recessions.

Prediction 2: We forecast a pattern where yield curve inversions - historically indicative of imminent recessions - precede a decline in momentum returns. Specifically, we expect to observe momentum crashes in the aftermath of such economic downturns. This prediction underscores the anticipated cyclical nature of the yield curve's influence on momentum returns.

Hypothesis 3: Market volatility, as measured by the VIX and volatility rankings of portfolios, is related to both momentum returns and portfolio performance.

Prediction 3a: We predict a positive correlation between periods of heightened market volatility (as reflected by the VIX index) and increased momentum returns. This suggests an expectation of investor compensation for additional risk taken on during volatile market conditions. Furthermore, we expect this correlation to elucidate the phenomenon of momentum crashes following periods of significant market volatility, particularly within the context of recessions.

Prediction 3b: We anticipate a noticeable impact of volatility on portfolio returns, where higher volatility results in greater fluctuations in returns and reduces risk-adjusted performance. This prediction emphasizes the importance of volatility in the risk-return trade-off in investment portfolios.

Further, we delve into the methodology utilized to test our three main hypotheses. The result from our methodology is later presented in our analysis.

3.2 Momentum Trading Strategy

To test our three predictions, we first must construct the momentum returns.
The momentum trading strategy is an implementation of using historical returns to predict the cross-section of future returns. This is typically implemented by creating a winner portfolio (portfolio consisting of stock that generated previous high returns) and a loser portfolio.

From there you proceed going long the winner portfolio and short the loser portfolio, generating a long-short momentum strategy. One can adjust the strategy by using different sorting periods, such as how long the look-back-period is and how long the holding period is. Momentum trading is well-documented for creating abnormal returns across multiple periods, in many markets, and numerous asset classes.

3.3 The Yield Curve

The yield curve, a graphical depiction of interest rates on debt for a range of maturities, is a fundamental instrument within financial markets, used by market participants and policymakers for various analytical and forecasting purposes. The curve reveals the relationship between the interest rate and the time to maturity of the debt for a given borrower in a given currency.

The yield curve is typically upward-sloping, signifying that long-term interest rates are higher than short-term interest rates. This configuration reflects the expectations theory that the interest rate for a long-term bond will be the geometric average of short-term interest rates expected to occur over the life of the long-term bond. The yield curve, which plots interest rates on bonds of varying maturity but similar credit quality, usually exhibits an upward slope, implying that long-term interest rates exceed short-term rates. This typical configuration can be understood through the lens of the expectations theory, which posits that the interest rate of a long-term bond should mirror the geometric average of the short-term interest rates projected to prevail over the tenure of the long-term bond.

According to the expectations hypothesis, the yield curve should ideally be flat, reflecting a situation where expected short-term rates are stable, and hence long-term rates—an average of future expected short-term rates—would not deviate significantly from current short-term rates.

However, the yield curve typically deviates from this theoretical flat profile in real-world markets. This discrepancy can primarily be attributed to various risk premiums that investors demand for holding long-term bonds. In economic expansions, for instance, investors may anticipate future short-term interest rate hikes by central banks to curb inflation, thus demanding higher long-term rates. Additionally, investors may also demand a term premium to compensate for the additional risk of holding long-term bonds, such as interest rate risk and inflation risk. These factors contribute to a yield curve that is not flat but instead upward-sloping during economic expansions. Thus, deviations from the expectations hypothesis—in the form of these additional risk premiums—result in a yield

Besides, this normal state of affairs reflects a risk premium for lending money over a longer time span, as lenders demand higher yields as compensation for interest rate risks and uncertainty over time (also known as the liquidity preference theory). However, during periods of heightened economic uncertainty or impending economic downturns, the shape of the yield curve can invert. In this case, short-term interest rates rise above long-term rates, reflecting the market's anticipation of lower interest rates in the future due to a likely slowdown in economic activity. Historically, such yield curve inversions have proven to be reliable predictors of recessions, causing them to be closely watched by both economists and investors alike.

In the context of our research, we initially employed the spread between the 10-year and 2-year Treasury yields, a commonly used measure in studies spanning extended periods. This spread is a conventional choice in macroeconomic studies, capturing the long-term economic outlook relative to the medium-term.

However, given our focus on the lead-up to and aftermath of financial crises, when market volatility tends to be high, we opted to modify our approach. We transitioned to using the spread between the 10-year and 1-year Treasury yields. This narrower spread provides a more sensitive barometer of short-term market fluctuations and enables a closer examination of market dynamics during these critical periods surrounding recessions.

It's worth noting that our empirical investigations do not reveal any significant differences in our analysis outcomes when using the 10-year minus 1-year spread compared to the 10-year minus 2-year spread. This finding reinforces the idea that the choice of spread depends largely on the specific research question and the dynamics one wishes to explore. Therefore, the 10-year minus 1-year spread, with its emphasis on shorter-term market sentiments, proves to be a suitable choice for our particular study.

3.4 Robustness Test

In our research, we employ a multiple regression analysis to test our hypothesis and examine the relationships between the variables of interest. Regression analysis is a powerful statistical tool that allows us to understand how the value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held constant. When risk-adjusting the momentum returns we use the 1 – month risk-free rate as used on the website of Kenneth R. French.

Our dependent variable in this research is the long-short return from the Momentum strategy. We seek to understand how this return is influenced by various independent variables: the yield curve (10 minus 1), the excess return of the market (MRP), the size (SMB) and value (HML), conservative minus aggressive (CMA), and robust minus weak (RMW) factors from the Fama-French five-factor model and market volatility (as measured by VIX). Our regression model can be formally expressed as follows:

$$Risk\ Adj.Long - Short\ Momentum\ Returns = \beta_0 + \beta_1 * Yieldcurve + \beta_2 * MRP + \beta_3 * SMB + \beta_4 * HML + \beta_5 * CMA + \beta_6 * RMW + \beta_7 * Volatility + \varepsilon$$

Where, β_0 is the y-intercept (constant term), β_1 through β_5 are the coefficients for each independent variable, representing the change in the dependent variable for a one-unit change in the respective independent variable, ε is the error term, representing the variation in the dependent variable that the model does not explain.

By examining the coefficient estimates (β's) and their statistical significance, we can determine which variables have a significant influence on the long-short return and in what direction (positive or negative). Furthermore, we can evaluate the goodness-of-fit of our model using R-squared and adjusted R-squared values.

This approach provides us with a robust and flexible method to study complex relationships in our data, enabling us to identify significant factors affecting the Momentum strategy's performance and possibly predict momentum crashes.

3.5 Fama French Five Factor Model

To deepen our understanding of the momentum strategy's performance and risk profile, we adopt a robust analytical approach using the Fama-French five-factor model. This model, conceived by finance scholars Eugene Fama and Kenneth French, enhances the simplicity of the Capital Asset Pricing Model (CAPM) by adding four supplementary factors that capture company size, value, investment and profitability dimensions.

The first factor, the Market Risk Premium, signifies the excess return gained from investing in a broad market portfolio, such as the S&P 500, as opposed to a risk-free asset, such as U.S. Treasury bills. This factor captures the systemic risk in the market, as acknowledged in the CAPM.

To better tailor the model to our analysis, we include the second factor, SMB (Small Minus Big). The SMB factor taps into the "size effect," an empirical observation that small-cap stocks often yield higher average returns than their large-cap counterparts. The third factor, HML (High Minus Low), further augments our analytical scope. The HML factor aims to encapsulate the "value effect," which notes that stocks with a high book-to-market ratio (value stocks) tend to outperform those with a low book-to-market ratio (growth stocks). CMA (Conservative Minus Aggressive) captures the effect of a company´s investment policy on its stock return, which reflects the differential between companies that have conservative investment strategies and the ones with aggressive investment strategies. The last factor, called RMW (Robust Minus Weak) captures the profitability factor which notes the difference between companies with robust profitability and the ones with weak profitability.

The role of Fama-French factors in our analysis is to provide robustness checks for our primary findings. By incorporating these factors, we can account for the risk factors that have been widely acknowledged in finance literature as influential on asset pricing. It allows us to control for systematic risks associated with size, value, profitability, investment, and overall market excess returns, which may affect the momentum returns independent of our variables of interest, i.e., the yield curve and volatility.

The Fama-French factors allow us to distill the effect of these risks, thereby helping us better isolate the specific influence of the yield curve and volatility on momentum returns. The "horse race" regression incorporating these factors alongside volatility and momentum serves to pit these effects against one another. It enables us to ascertain which of these effects has more predictive power or influence over the momentum returns.

In essence, risk-adjusting our analysis using the Fama-French factors enhances the validity of our findings by ensuring that the observed relationships are not spurious or confounded by uncontrolled risk factors. Thus, this ensures our study's conclusions are as accurate and robust as possible. This approach will enable us to derive insights that are more reliable and applicable to the real world, strengthening the overall value and impact of our research.

4.0 Data

To carry out the analysis of this paper, we collect monthly historical data on US stock data, return on US T-bonds, Factor Model, and risk factors from July 1941 to January 2020. The time frame from July 1941 to January 2020 offers a robust dataset across diverse market conditions, encompassing significant economic cycles and regulatory changes. This expansive period enhances the validity of your statistical results, provides in-depth insights into long-term risk-return tradeoffs, and allows comprehensive benchmarking of Fama-French factors across a multitude of market scenarios. We have only succeeded in obtaining data from February 1990 to January 2020 for the Volatility Index (VIX), sourced directly from CBOE.

4.1 US Stock Data

Stock data from the US stock market is collected from The Center for Research in Security Prices (CRSP) through Wharton Research Data Services (WRDS). The data includes price, return information, and shares outstanding.

Table 1: **Stock data**

The table demonstrates average and median values for stock returns and shares outstanding, culled from an initial set of 4,477,937 observations. Post exclusion of non-applicable entries, the final analysis incorporates 4,301,366 observations for returns and 4,442,207 for shares outstanding, providing a robust basis for examining momentum returns across various market conditions.

	Return	**Shares outstanding**
Average	1.08%	43443
Median	0.01%	8078
Observations	4 301 366	4 442 207

Embracing the broader U.S. stock market for extended analysis, as opposed to strictly the S&P 500, provides a richer and more resilient perspective. This approach absorbs the fluctuations in the constituents of indices such as the S&P 500, ensuring consistency and inclusivity in the study across extensive periods. In the analytical framework of this report, our primary focus is to harness the available stock data by calculating the monthly momentum returns for each individual stock. Subsequently, these stocks will be segmented into portfolios correlating to their respective momentum returns. Once we have momentum portfolios, we will be able to sort them based on the slope of the yield curve and volatility enabling the comprehensive investigation of risk-return profiles across diverse market conditions.

4.2 US Treasury Bonds

To best analyze the performance of the momentum portfolios sorted by yield curve slope we collect historical yield returns for 10-year and 1-year treasury yields with constant maturity from CRSP Treasuries – Fixed Term indices. Return on treasury yield have no missing values, which is why we use 1941 as the starting point of our analysis. This allows us to conduct an uninterrupted long-term analysis. This ensures that our study captures a wide array of economic conditions, further strengthening the robustness of our findings. The decision to utilize 10-year and 1-year bonds serves two main purposes. First, these two maturities effectively capture the long and short ends of the yield curve, providing a comprehensive view of its slope. Second, the 'term spread' created by this 1-year vs. 10-year bond difference is not only a conventional measure of the yield curve's shape but also a reliable indicator of economic activity.

Table 2: **Yield curve**

Depicting the average and median returns of 10-year, 2-year, and 1-year U.S. Treasury bonds, the table draws from a starting pool of 1164 observations, with 221 non-applicable entries. The data from the remaining 943 observations facilitate a comprehensive understanding of historical yield dynamics. This threefold bond perspective strengthens our exploration of the yield curve's impact on momentum portfolio returns.

	1-year	**2-year**	**10-year**
Average	0.374%	0.239%	0.256%
Median	0.262%	0.239%	0.256%
Observations	943	943	943

The yield curve, illustrating the relationship between interest rates and the time to maturity of interest-bearing securities, serves as a crucial macroeconomic indicator. It provides insights into market participants' expectations of future interest rates, thus indirectly reflecting their sentiment toward future economic growth. By sorting the momentum portfolios according to the yield curve slope, we aim to unravel the dynamics between economic conditions, as approximated by the yield curve, and the performance of momentum investing strategies. This novel approach should enrich the existing financial literature on momentum portfolios and offer valuable insights for investment practices.

4.3 Factor Model

To provide a robust framework for explaining the cross-sectional variations in stock returns we chose to include Fama-French factors, which include market risk, SMB, HML, RMW and CMA. Fama-French factors are collected from Wharton Research Data Services. These factors capture systematic risks that cannot be diversified away and therefore command a risk premium. Momentum returns, the tendency of stocks that perform well in the past to continue their outperformance, are empirically robust anomalies that traditional asset pricing models struggle to explain. Moreover, the Fama-French factors present a potential explanation for momentum returns, as these returns could be interconnected with the same underlying risks these factors capture. For instance, it can be hypothesized that smaller firms, as represented by the SMB factor, may experience heightened momentum returns due to the amplified business risks and uncertainties they encounter compared to their larger counterparts. Likewise, value stocks, represented by the HML factor, which typically feature lower valuations, often a result of less promising prospects, may manifest stronger momentum effects as the market's perception of their future prospects undergoes shifts over time.

Table 3: **Factor Model**

The table elucidates the mean, median, and number of observations for Fama-French factors and the momentum factor. These factors—excess return, SMB, HML, RMW, CMA, and risk-free rate — are integral to capturing systematic risks in stock returns and providing potential explanations for momentum returns. This analysis further allows for a comprehensive understanding of how these factors and their inherent risks influence cross-sectional variations in stock returns. RMW and CMA have 401 observations as we only regress these against the VIX Index from 1990 to 2020.

	Excess Return	**SMB**	**HML**	**RF**	**RMW**	**CMA**
Average	0.696%	0.169%	0.365%	0.306%	0.342%	0.195%
Median	1.07%	0.09%	0.23%	0.27%	0.37%	0.00%
Observations	943	943	943	943	401	401

4.4 Volatility Index

Directly sourced from the Chicago Board Options Exchange, VIX provides real-time market volatility expectations from 1990 to 2020. Derived from the S&P 500 index options, it reflects market sentiment about anticipated volatility. We leverage the VIX with our momentum portfolios to explore intricate relationships between market volatility and momentum returns.

We process the VIX data, adjusting date fields to match our momentum return data. After aligning the date ranges, we merge the datasets based on date, offering a synchronized examination of momentum portfolios under concurrent volatility conditions. Further, we calculate the VIX change and employ it as an independent variable in a linear regression model to quantify its influence on our momentum portfolios' long-short returns. By dividing the merged dataset into five portfolios based on VIX change, we assess how distinct volatility levels impact portfolio performance. This division and the ensuing calculation of average long-short return per portfolio help us extract insightful details about the volatility-momentum return relationship.

In subsequent analyses, we introduce a lagged version of the VIX change, aiming to account for any delayed effects of volatility changes on our momentum portfolios. The outcomes from this comprehensive analysis contribute significant context to the scholarly dialogue surrounding momentum returns and their association with market volatility as captured by the VIX.

4.5 Data Collecting Criticism

In our study, we are tasked to develop our own measure of volatility due to the unavailability of the VIX index for the entire period from 1941-2020. We employ a straightforward approach to calculate the 12-month volatility. This measure is designed to capture the inherent riskiness associated with each stock, with higher volatility indicating higher risk. However, this method is not without its drawbacks. Our approach, which assumes past volatility predicts future volatility, has limitations. Changes in market dynamics and external factors could make past volatility an inaccurate risk indicator, especially since our method focuses solely on price movements, neglecting sources of risk like market sentiment and macroeconomic indicators. Additionally, our measure, based only on historical data, could fall short in capturing shifts in volatility influenced by changing investor sentiment, unlike the VIX index which includes option price information and presents a more comprehensive view of market volatility. Moreover, creating our own volatility measure could lead to errors due to computational constraints or data inaccuracies, unlike the well-established VIX index, backed by a sophisticated methodology and a reputable financial institution.

Despite these limitations, we believe that our approach provides a reasonable approximation of stock-level volatility, given the constraints and the breadth of the period we are examining.

5.0 Analysis

In this section, we delve into our research findings, examining the relationship between the yield curve, volatility, and the success of momentum trading strategies. Our analysis starts with our first prediction, looking at the relationship between the yield curve and momentum returns. Here, we created momentum portfolios and analyzed their performance against changes in the yield curve, aiming to confirm or debunk the existence of a noticeable correlation between these factors.
Next, we move to our second prediction, investigating the relationship between yield curve inversions and momentum returns around recession periods. Using box plots, we compare momentum returns before and after recessions, striving to understand if yield curve inversions anticipate significant decreases in momentum returns.

Finally, we focus on the impact of market volatility on momentum returns, testing momentum portfolios based on both stock-specific volatility and the VIX index. This part of the analysis explores the potential positive correlation between high volatility periods and increased momentum returns, while also probing into the occurrence of momentum crashes following these turbulent periods.
Overall, each section of this analysis helps confirm or deny our predictions and offers valuable insights into the intricate dynamics of the financial market.

5.1 Creating the Momentum Returns

In our study, we follow a strategic approach to compute monthly momentum returns. Following the footsteps of the empirical literature (Jegadeesh and Titman, 1993; Asness, 1994; Fama and French, 1996), we initially sort the returns over a period spanning from month t-12 to t-2. We specifically opt for this sorting period to avoid the influence of short-term reversal effects, as documented by Jegadeesh (1990) and Lehmann (1990).

Subsequently, based on the sorted returns, we create 10 portfolios. Each portfolio is assigned a rank, where '1' denotes the portfolio with the lowest returns (losers) and '10' denotes the portfolio with the highest returns (winners). It's interesting to note that our portfolio returns are generally monotonically increasing, although we do observe a slight dip between the returns of portfolios 2 and 3.

For the next phase, we construct a long-short strategy. This strategy consists of buying the winner portfolios and selling the loser portfolios. The difference in the returns between the winner and loser portfolios offers us the returns of this long-short strategy. Finally, to summarize the performance of our strategy, we compute the average monthly return from the long-short strategy.

Our results show an average monthly momentum return of approximately 0.686%, which aligns well with the findings in the existing literature.
This approach not only lets us exploit the momentum premium, a recurring concept in financial studies, but also ensures that our methodology is grounded in, and compatible with, established research in this domain.

Table 4: **Momentum returns**

The table highlights the average monthly returns for 10 portfolios, each ranked based on prior return patterns. Showing an intriguing, almost monotonic increase from Portfolio 1 to 10, these findings attest to the profitability of a long-short strategy, aligning with the momentum premium established in financial literature. This underlines momentum investing's potential in harnessing returns in varying market conditions.

Portfolio	**Average Monthly Return**
1	0.9637 %
3	1.0763 %
2	1.1118 %
4	1.1596 %
5	1.2331 %
6	1.2474 %
7	1.3165 %
8	1.3936 %
9	1.4727 %
10	1.6450 %

5.2 Plotting the Yield Curve against Momentum Returns

In our study, we delve into the interplay between the yield curve and momentum returns, seeking to establish whether the yield curve acts as an indicator of momentum returns. For our analyses, we compute the yield curve by calculating the spread between 10-year and 1-year Treasury rates, a widely accepted method. This yield curve is sorted against momentum returns in our plots to better visualize their relationship.

For a more nuanced understanding, we segment the yield curve into four distinct intervals, extending from negative to positive. These intervals are subjected to various tests to measure their potential impact on momentum returns. We start our analyses with simultaneous yield curve intervals, followed by lagged intervals, and finally, we explore the forward yield curve.

Interestingly, our observations indicate that both simultaneous and lagged yield curves manifest returns in the sequence of intervals 1 – 3 – 2 – 4. However, when we extend our test to include a 2-month forward yield curve, we note an improvement in our results. This scenario presents a monotonically increasing momentum return, offering intriguing insights.

To further validate the predictive power of the yield curve, we adjust the forward period from 1 to 12 months. This exploration reveals that the yield curve's predictive prowess caps at a 2-month forward period. Beyond this, its ability to foresee momentum returns diminishes, a finding that resonates with existing literature highlighting the limitations of the yield curve's predictive reach. This facet of our research reaffirms the importance of understanding the temporal boundaries of financial predictors, ensuring robust and reliable analyses.

Table 5: **2-Month Forward Yield Curve**

The table showcases the intriguing link between momentum returns and distinct segments of a 2-month forward yield curve. It succinctly illustrates a transition from negative to progressively positive momentum returns across four yield curve categories, thereby accentuating the predictive implications of the yield curve in momentum investments.

Yield Curve Category 2-Months Forward	**Average Momentum Returns**
1	-4.5572 %
2	-0.1107 %
3	0.7335 %
4	1.0296 %

5.3 Plotting Yield Curve and Momentum Before and After Recessions

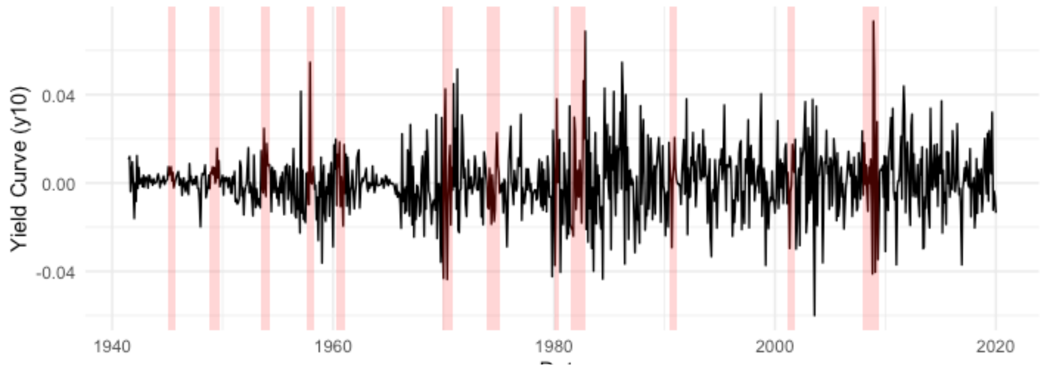
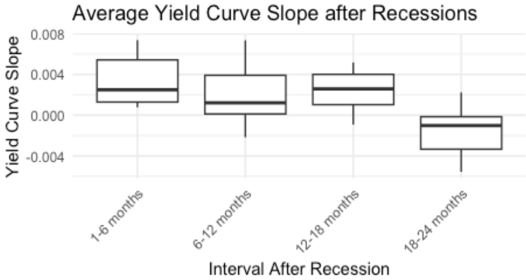


Figure 1: Yield Curve over Time Highlighting Recessions

Research suggests that inverted yield curves can be predictive indicators of impending recessions. Considering this, our study aims to examine the relationship between the yield curve and momentum returns within the context of these economic downturns. Specifically, we focus on the two-year periods preceding and following each recession.

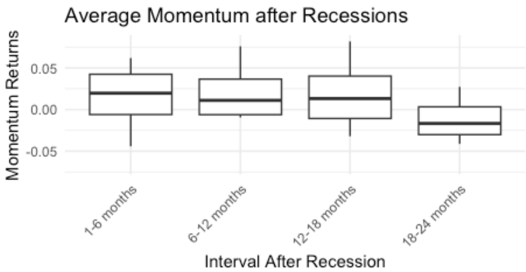
In our dataset's timeframe, there have been twelve periods classified as recessions in the United States according to the National Bureau of Economic Research (NBER). While a common rule of thumb is to define a recession as two consecutive quarters of negative GDP growth, we refer to the NBER's definition, which describes a recession as a significant, widespread decline in economic activity lasting more than a few months, as indicated by measures including real GDP, real income, employment, industrial production, and wholesale-retail sales. To perform our analysis, we first calculated the average yield curve and momentum returns for four distinct intervals. These intervals were set at 1-6, 6-12, 12-18, and 18-24 months, respectively, both prior to and following each recession.

By analyzing these different time frames, our investigation seeks to uncover any discernible patterns or correlations between the state of the yield curve and momentum returns around periods of economic downturn. This approach enables us to gain a more nuanced understanding of the yield curve's predictive power in relation to recessions and its potential influence on momentum-based investments strategies.



Average Yield Curve Slope after Recessions				
Months	1-6	6-12	12-18	18-24
Slope	0.3406%	0.2033%	0.2402%	0.1555%

Figure 2: Average Yield Curve Slope after Recessions



Average Momentum Returns after Recessions				
Months	1-6	6-12	12-18	18-24
Returns	1.5472%	1.0187%	1.7811%	-1.1939%

Figure 3: Average Momentum after Recessions

5.4 After Recessions

The results show that momentum seems to crash in the period of 18-24 months post recessions. It is also interesting that the momentum returns seem to follow a similar path to the yield curve after a recession indicating a positive relationship between them.

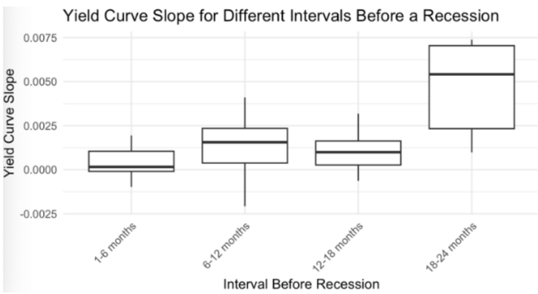
Based on the evidence from Cooper, Gutierrez, and Hameed (2004) and Stivers and Sun (2010), they suggest that momentum premiums tend to decrease under conditions of negative past three-year market returns and high market volatility.

While these conditions are often associated with recessions, these studies do not explicitly link the timing of momentum crashes to the aftermath of recessions. Our finding that momentum crashes occur 18-24 months post-recessions adds a new temporal dimension to these earlier studies. It indicates that while momentum premiums might decrease during periods of high volatility and negative returns (often during or leading up to recessions), the actual momentum crash might not materialize until the economy begins to recover.

This could be due to a delay in the adjustment of market participants to changing economic conditions, or it could be an artifact of some other intervening variable not considered in these prior studies. Either way, our results contribute to the existing body of knowledge by specifying a time frame for when momentum crashes are likely to occur after a recession, which was not directly addressed in the aforementioned studies.

5.5 Before Recessions

Research on market trends leading up to a recession is limited, especially when it comes to momentum returns and changes in the yield curve. In our study, we aimed to examine these factors in the two years before a recession to see if they can help predict economic downturns.



Average yield curve slope before recessions

Months	1-6	6-12	12-18	18-24
Slope	0.3406%	0.2033%	0.2402%	0.1555%

Figure 4: Yield Curve Slope for Different Intervals Before a Recession

Average momentum before recessions

Months	1-6	6-12	12-18	18-24
Slope	1.5644%	1.0477%	-0.1503%	0.2974%

Figure 5: Average Momentum Returns Before a Recession

Our findings show a trend in the yield curve's slope, which tends to decrease as a recession nears. This aligns with previous research suggesting that an inversion of the yield curve often happens before recessions.

When looking at momentum returns, we observe a similar anticipatory trend. In the 6 months leading up to a recession, average momentum returns drop to -1.5644%. This could indicate that as investors foresee economic instability, they may adjust the periods they use the strategy, leading to a reduction in the effectiveness of momentum-based strategies and a decrease in their returns.

Contrarily, in the 6-12 months before a recession, momentum strategies seem to capture the market's adjusting behaviors with average returns of 1.0477%. This suggests that during this period, momentum strategies are better positioned to capitalize on the trends and price movements that often precede a downturn.

The relatively smaller negative momentum returns observed during the 12-18 months (-0.1503%) and 18-24 months (-0.2974%) before a recession indicate that the momentum strategy's performance during these periods is less consistent. This could be due to a variety of factors, including broader market trends and the complex nature of economic cycles.

In conclusion, our findings demonstrate that momentum strategies exhibit variable performance across different periods preceding a recession, mirroring trends seen in the yield curve's slope. This suggests that the behavior of momentum returns, and yield curve inversions may be interconnected elements of the market's broader anticipatory response to an impending recession. As always, these insights should be considered as part of a holistic approach to market analysis, considering a wide range of economic indicators and market conditions.

5.6 Deep Dive into three separate Recessions

The observed decline in momentum returns in the 18-24 months following a recession sparked our interest and led us to delve deeper. Specifically, we were intrigued to understand whether this pattern could be attributed to the unique double-dip recession in the 1980s or whether it might be influenced by other notable recessions of greater severity.

In the 1980s, the economy experienced two closely spaced recessions, which are collectively referred to as the "double dip" recession. This unusual economic scenario could have exerted distinct effects on momentum returns, potentially explaining the observed downturn 18-24 months post-recession. Alternatively, it could be that recessions of larger magnitude, such as the economic downturn following the dot-com bubble burst or the Great Recession of 2008, might have exerted more substantial influences on momentum returns that deviate from the average results observed.

By investigating these specific periods, we aim to discern patterns that might not be immediately evident when studying the average behavior of momentum returns. This could provide valuable insights into the dynamic nature of momentum investment strategies in response to varied and severe economic conditions. In doing so, our research would contribute to a more nuanced understanding of how different types of recessions can impact the performance of momentum-based strategies.

To better understand the behavior of momentum returns following a recession, we have chosen to study unique recessionary periods, namely, the double-dip recession in the early 1980s, the recession following the burst of the dot-com bubble in the early 2000s, and the Great Recession following the 2008 financial crisis. These episodes provide contrasting economic environments that could significantly influence momentum returns.

Our analysis thus extends to investigating how these distinct recessionary periods affect momentum returns and contributes to the literature by examining these extraordinary events and their impact on momentum investment strategies.

Double Dip Recession

The double-dip recession, which occurred from January 1980 to July 1980 and from July 1981 to November 1982, represents an intriguing case. Previous studies show that momentum returns tend to decline substantially 18 to 24 months after a recession.

We hypothesize that the double-dip nature of the 1980s recession might have accentuated this effect, extending the period of depressed returns due to the recurrent negative shock to the economy. The two consecutive recessions may have induced prolonged pessimism in the market, affecting the efficacy of momentum strategies.

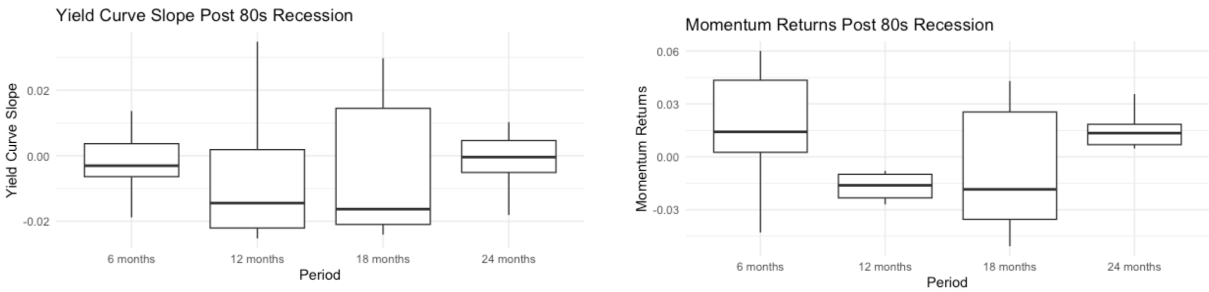
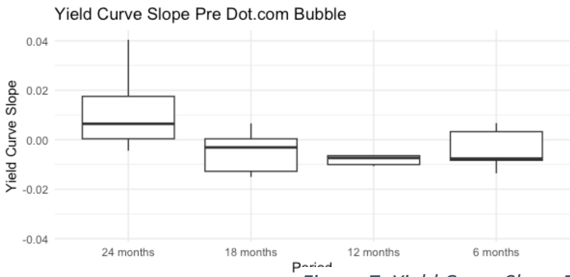


Figure 6: Yield Curve Slope and Momentum Returns Post 80s Recession

Our investigation utilizes box plots that begin at the conclusion of the first recession in 1980 and extend to the onset of the succeeding recession, which commenced 12 months after the termination of the first. Despite the unique circumstances of the double-dip recession, we observe a consistent pattern in which momentum returns seem to mirror the behavior of the yield curve following recessions. Interestingly, the significant downturn in momentum returns that we have typically observed does not appear to be an outcome of this double-dip recession.

Dotcom Bubble

The dot-com bubble burst, culminating in a recession from March 2001 to November 2001, presents another distinct economic event. The speculative excesses of the period and their subsequent fallout may have created unique dynamics in momentum returns, which we intend to explore.



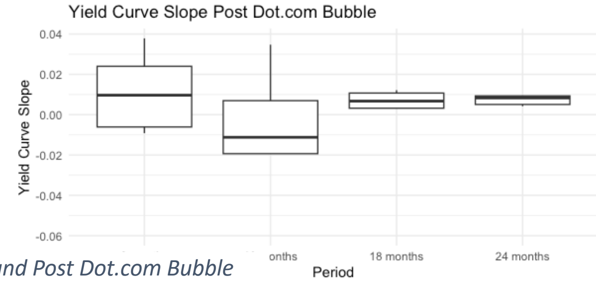


Figure 7: Yield Curve Slope Pre and Post Dot.com Bubble

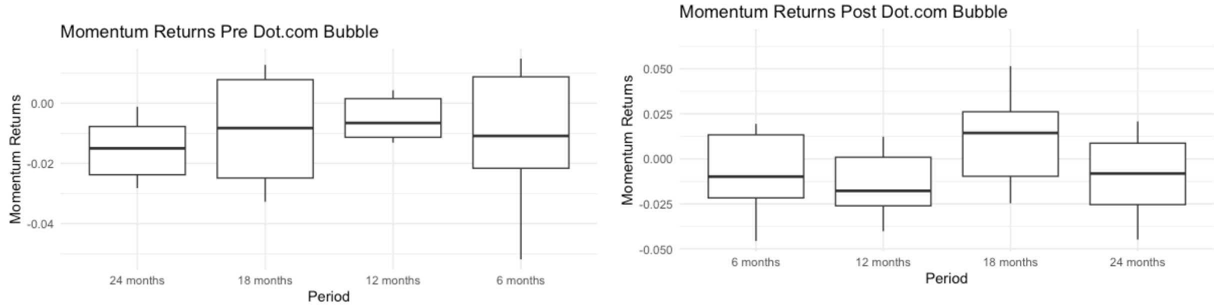


Figure 8: Momentum Returns Pre and Post Dot.com Bubble

In the context of the dot-com bubble burst and its ensuing recession, our examination of the yield curve and momentum returns offers compelling insights. Our analysis indicates that the yield curve, as anticipated, exhibits a declining trajectory starting from 24 months pre-recession and culminating in the recession onset.

This corresponds with established economic theories suggesting an impending recession is usually foreshadowed by yield curve inversions or flattening, reflecting investors' pessimistic expectations of future economic conditions. In the post-recession period, the yield curve experiences an upswing, marking an anticipated cyclical recovery. However, it undergoes a transitory contraction before stabilizing in the 12-24 months post-recession interval. This might be indicative of the economy undergoing corrections and calibrations in response to previous overestimations of growth potential.

Concurrently, momentum returns manifest relative stability in the run-up to the recession, albeit with a slight contraction immediately preceding the economic downturn. This could be a consequence of market participants readjusting their positions in anticipation of potential adversities, dampening the effectiveness of momentum strategies. In the aftermath of the dot-com bubble burst, momentum returns are significantly suppressed during the initial year, potentially reflecting persistent market dislocations and prevailing risk aversion in the aftermath of a severe sector-specific correction.

However, a moderate recuperation in momentum returns is observed in the 12–18-month post-recession interval, suggesting a partial market recovery and the reestablishment of previously profitable momentum strategies. Notably, a contraction in momentum returns is evident at the 24-month mark, suggesting potential market recalibrations or a reversion to a lower return environment.

Financial Crisis

Finally, we turn our attention to the Great Recession of December 2007 to June 2009, following the 2008 financial crisis. The severity and global nature of this recession, accompanied by a significant financial system disruption, could have implications on the momentum returns beyond those observed in less severe recessions.

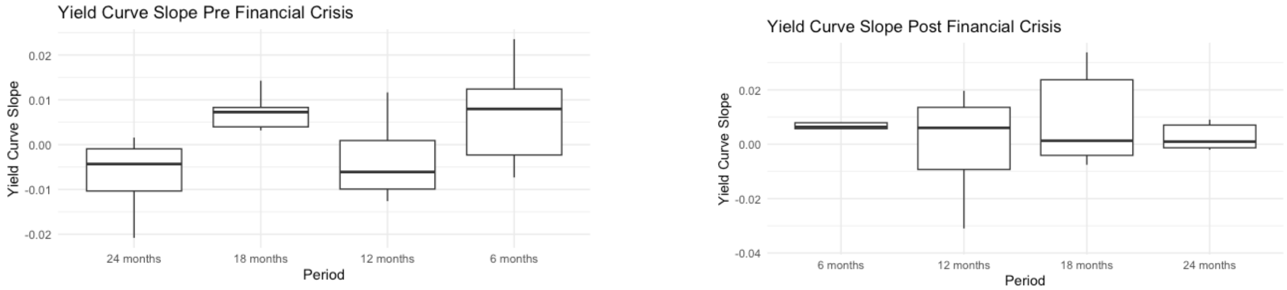


Figure 9: Yield Curve Slope Pre and Post Financial Crisis

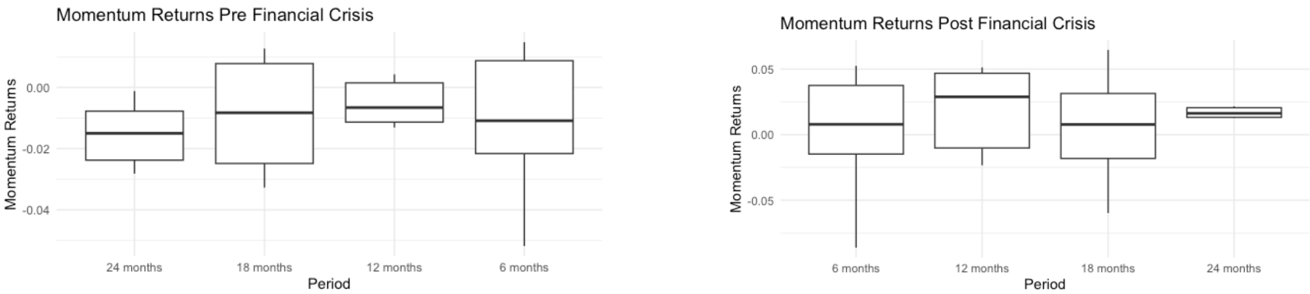


Figure 10: Momentum Returns Pre and Post Financial Crisis

The yield curve behavior in the lead up to the Great Recession presents interesting insights. If we scrutinize the period through a wider lens, using six-month intervals, the yield curve appears to be on an incline. This observation aligns with the inherent financial volatility characterizing this tumultuous time. On the surface, this trend might suggest a strengthening economic outlook. However, it is essential to take into consideration that these spikes may reflect heightened market uncertainty rather than genuine economic growth.

A more nuanced understanding emerges when we adjust our perspective to a finer scale. When we examine the yield curve at one-month intervals, a different picture emerges. This granular view reveals a marked downward trend in the yield curve during the month leading up to the onset of the recession. This trend is indicative of investors' declining confidence in the economic outlook and could be considered a precursor warning of the impending recession.

Table 6: **VIX Impact on the Momentum Return**

The table delves into the intriguing correlation between market volatility (VIX) quartiles and momentum returns. It manifests that during high volatility states, such as Portfolio 4, momentum strategies outperform, while in low volatility periods, represented by Portfolios 1 and 2, these strategies underperform. This trend emphasizes the influential role of market volatility in shaping momentum-based investment strategies.

Portfolio	**Observations**	**Mean**	**SD**	**Median**
1	100	-0.2188%	0.0226	-0.4630%
2	100	-0.1890%	0.0287	-0.1700%
3	100	0.1764%	0.0482	0.2700%
4	100	2.1540%	0.0841	1.8400%

The impact of the VIX on momentum returns is an important consideration for investors. Momentum investing strategies often rely on the idea that assets which have performed well in the past will continue to do so in the future. This analysis investigates the relationship between the expected market volatility, as measured by VIX, and the returns generated by a momentum-based investment strategy.

The data is segmented into four portfolios based on quartiles of VIX values. Portfolio 1 represents the lowest 25% of VIX values, indicating periods of low market volatility. Conversely, Portfolio 4 represents the highest 25% of VIX values, associated with high market uncertainty.

The results show varied momentum returns across different volatility states. Portfolio 1, with the lowest VIX values, records a mean return of -0.2188% and a median return of -0.4630%. This implies that during periods of low market volatility, momentum strategies tend to underperform. Portfolio 2, representing the second quartile of VIX values, also records negative mean and median returns (-0.1890% and -0.1700% respectively), indicating a similar trend as observed in Portfolio 1.

However, the trend shifts with Portfolio 3, which displays positive mean and median returns (0.1764% and 0.2700% respectively), suggesting that momentum strategies start to yield positive returns as market volatility increases. The pattern is more pronounced in Portfolio 4, comprising the highest VIX values, where the mean and median returns are significantly positive (2.1540% and 1.8400% respectively). This indicates that momentum strategies tend to perform well during periods of high market volatility.

Overall, the analysis indicates that the VIX levels can significantly influence the returns from momentum investing strategies. High VIX values, which correspond to periods of greater market uncertainty, tend to coincide with higher momentum returns. On the other hand, low VIX values, suggestive of low market volatility, generally result in lower momentum returns. This relationship highlights the importance of considering market volatility when employing a momentum-based investment strategy. Further research could investigate the mechanisms behind this relationship, including the specific asset classes involved and the role of market participants' sentiment.

Daniel and Moskowitz (2016) show that momentum profits are higher in times of high market volatility. They attribute this to the "slow information diffusion" hypothesis, where news travels slowly across investors, causing a delay in price adjustments and therefore creating momentum.

Conversely, during periods of low volatility, there may be less "news" or information to diffuse, resulting in less pronounced momentum effects. This is in line with your analysis showing negative momentum returns in Portfolios 1 and 2, which represent periods of low market volatility.

5.7 Explanatory Analysis of the Impact of Volatility on Portfolio Returns

We engage in an exploratory analysis of volatility portfolios to comprehend their performance dynamics. The focus is to dissect and comprehend the influence of volatility on portfolio returns. Initially, we calculate a 12-month volatility with a T-2 to T-12 sorting period. For this, we create volatility portfolios by ranking the 12-month lagged volatility. The data is grouped by unique identifiers, and by month, allowing for a comprehensive examination of volatility across time and entities.

This process is accompanied by the integration of the yield curve data with our existing dataset. We accomplish this by merging the slope of the yield curve with the volatility data, ensuring no missing values were present in the volatility rank after the merge. Once the dataset is prepared, we calculate portfolio returns for these volatility portfolios. This step is critical in aligning our research with the objective of understanding the relationship between volatility and portfolio returns.

Our performance analysis highlights intriguing insights. We compare the performance of portfolios sorted by their volatility ranking. The performance metrics include annualized return, annualized volatility, and the Sharpe ratio—a measure of risk-adjusted return.

Table 7: **Explanatory Analysis**

The table presents a detailed exploratory analysis of the performance metrics across ten volatility portfolios. Key performance indicators, including annualized return, annualized volatility, and Sharpe ratio, were analyzed to understand the influence of volatility on portfolio returns. The analysis revealed that portfolios with moderate volatility rankings often provided the highest returns, and higher volatility corresponded to greater return fluctuations and diminished risk-adjusted performance. The table below elaborates these observations further.

Volatility rank	**Annualized Portfolio Return**	**Annualized Portfolio Volatility**	**Sharpe Ratio**
1	0.103	0.110	0.752
2	0.110	0.240	0.377
3	0.146	0.144	0.807
4	0.151	0.157	0.830
5	0.151	0.171	0.767
6	0.144	0.182	0.680
7	0.146	0.201	0.625
8	0.140	0.225	0.533
9	0.126	0.254	0.417
10	0.109	0.315	0.283

The performance metrics exhibit the following trends across the ten volatility portfolios:

- The annualized returns show a fluctuating trend, peaking at the 4th and 5th ranked portfolios. This observation suggests that portfolios with moderate volatility rankings tend to achieve the highest annualized returns.
- The annualized volatility, as expected, increases with higher volatility rankings. This increase signifies that higher volatility portfolios exhibit more significant fluctuations in returns.
- The Sharpe ratios demonstrate a generally decreasing trend as the volatility rank increases, suggesting that portfolios with lower volatility rankings offer better risk-adjusted returns.

Findings underline the substantial impact of volatility on portfolio returns, with higher volatility leading to increased fluctuations in returns and reduced risk-adjusted performance. These findings contribute to the broader understanding of the risk-return trade-off in investment portfolios.

5.8 Multi-Factor Analysis of Portfolio Returns and Volatility Measures

We perform a multi-factor analysis on a dataset comprising of portfolio returns and volatility measures, with the aim to understand the impact of volatility index changes on long-short trading strategy returns, size-based portfolios, market factors and yield curve on portfolio returns.

In the first part of the analysis, we build a linear regression model where the response variable is the long-short return, and the predictor is the change in the VIX. The model shows no significant relationship between the VIX change and the long-short return (p-value = 0.835).

In the second part of the analysis, we create portfolios based on size (small-cap or large-cap) and calculate the Small Minus Big (SMB) factor, along with the market factor (Market Return - Risk-Free Rate). We also include the yield curve measure and the volatility factor based on the long-short strategy on high and low volatility portfolios.

Table 8: **Multi-factor Analysis**

The following table summarizes our multi-factor analysis aimed at comprehending the effects of volatility index variations, SMB factor, yield curve, and market factors on portfolio returns. Linear regression models indicated insignificant correlations between VIX changes and long-short return, whereas SMB, yield curve, and volatility factors demonstrated substantial impacts on portfolio returns. The table below provides a detailed account of these findings.

	SMB	**Market factor**	**Yield Curve**	**Volatility**
Average	-28.90%	-0.04%	48.44%	51.15%
Std. Error	1.88%	0.02%	3.65%	0.81%
T-value	-15.38	-1.79	13.26	62.88

The regression model shows a significant impact of SMB, yield curve and volatility factors on portfolio returns (p-value < 2.2e-16). The market factor shows less impact on the portfolio return (p-value = 0.0731).

From these results, we observe that the volatility, SMB, and yield curve factors are major contributors to the returns of portfolios, and the changes in the VIX do not significantly influence the returns from a long-short strategy based on volatility rankings.

Impact of Yield Curve slope on Long-Short Returns

In order to understand the connection between the slope of the yield curve and long-short returns, an analysis is carried out where we categorize the yield curve slopes into different intervals and calculate the average long-short return for each category. Initially, we partition the slopes into three categories: flat, negative, and upward. We then delve into a more nuanced categorization, splitting the yield curve slopes into smaller intervals, specifically 0.02 and 0.01 intervals, yielding more granular slope categories.

Once the categories were defined, we proceed to compute the average long-short returns for each. This methodology provides us with an empirical basis for analyzing the yield curve's impact on returns.

However, upon using the more granular 0.02 and 0.01 intervals, a wider range of returns emerges. For the 0.02 intervals, returns varied from 0.00483 (slightly positive) to 0.0148 (very positive). When the 0.01 intervals are used, the returns span from 0.00287 (positive) to 0.0110 (very negative/very positive).

Table 9: **Slope Category**

The table illustrates the influence of more precise slope categorizations on long-short returns. Notably, both extremely positive and negative slopes yield higher returns, adding a nuanced layer to the yield curve's role in shaping investment outcomes.

Portfolio	**Slope category**	**Average momentum returns with 0.01 interval**	**Average momentum returns with 0.02 interval**
1	Flat	0.0067	0.0067
2	Negative	0.0054	0.0077
3	positive	0.0029	0.0101
4	Slightly positive	0.0057	0.0048
5	Very negative	0.0110	0.0087
6	Very positive	0.0110	0.0148

In reflecting on these findings, we observe that the yield curve slope can impact long-short returns, with markedly high returns occurring when the yield curve is either very positive or very negative. This understanding can be utilized in refining investment decisions and formulating financial strategies.

Robustness Analysis of Market Factors

To delve into the complex interaction between assorted market factors and adjusted long-short returns, a robust linear regression model is leveraged. The dependent variable, in this case, is the adjusted long-short return, with independent variables encapsulating volatility, excess return, the size factor, the value factor, investment factor, profitability factor and the yield curve. The RMW factor represents the profitability premium, which is the difference in returns between firms with robust (high) and weak (low) operating profitability. This inclusion is predicated on the notion that highly profitable firms tend to generate superior momentum returns. This factor aids in investigating the profitability persistence in momentum returns and provides a more nuanced understanding of its underlying mechanisms.

The CMA factor, on the other hand, embodies the investment premium - the difference in returns between firms that are conservative and aggressive with respect to their investment behavior. It is based on the empirical observation that companies that invest conservatively tend to have higher returns than those that invest aggressively. By incorporating this factor, our model can scrutinize the influence of corporate investment behavior on momentum returns.

By extending our model to include these two factors, we aim to capture a more holistic representation of the complex dynamics governing momentum returns. Consequently, these enhancements should render our model more robust and provide more accurate and comprehensive insights, facilitating a deeper understanding of momentum trading strategies.

Table 10: **Regression Analysis of Market Factors**

The table details the regression results for assorted market factors against adjusted long-short returns. Significant coefficients for Rf (1.206935, direct), Volatility (0.261025, direct), Forward Yield Curve (0.162066, direct), and SMB (-0.2561, inverse) indicate their impact on returns. However, Excess Return, HML, RMW, and CMA, despite smaller coefficients, lack statistical significance. The standard errors range from 3.3522% to 58.6186%. These findings emphasize the influential role of Volatility, risk-free rate, Yield Curve and SMB in returns.

	Estimate	**Std. error**	**t-value**
Intercept	0.0011	0.28%	0.400
Excess Return	0.0231	4.51%	0.511
2-month Forward Yield Curve	0.1621	9.34%	0.084
Rf	1.2069	58,62%	2.059
SMB	-0.2889	6.91%	-4.182
HML	0.1216	7.69%	1.583
RMW	0.1364	8.75%	1.559
CMA	-0.0912	11,67%	-0.782
Volatility	0.2610	3.35%	7.787

The regression analysis for various market factors against the adjusted long-short returns gives us an in-depth understanding of the effects of each factor on returns. It is important to note that each factor, despite its coefficient size, may have different levels of statistical significance.

The model's intercept is estimated at 0.001104 with a standard error of 0.002758, implying that in the absence of other predictors, the expected adjusted long-short returns would approximately be 0.001104.

The coefficient of 'Excess Return' is calculated at 0.023038, but given its t-value of 0.511, it fails to reach significance at conventional levels, indicating its negligible influence on the adjusted long-short returns.

The '2-month Forward Yield Curve', has a coefficient of 0.162066. The t-value of 1.732 signals its significance at the 10% level (p-value: 0.0838), suggesting that changes in the yield curve have a non-negligible impact on the adjusted long-short returns. The variable 'R_f' has a coefficient of 1.206935 and a p-value of 0.0399, thereby statistically significant at the 5% level. This indicates a substantial direct relationship with the adjusted long-short returns.

The 'SMB' variable holds a significant inverse relationship with the adjusted long-short returns, with a coefficient of -0.288940 and a p-value less than 0.001. Despite the 'HML' and 'RMW' factors bearing coefficients of 0.121607 and 0.136377, respectively, their t-values do not reach statistical significance at traditional levels, suggesting that these factors do not meaningfully contribute to the variance in the adjusted long-short returns. The variable 'CMA' demonstrates a negative coefficient of -0.091222 but fails to achieve statistical significance. Notably, the 'Volatility' variable is significant with a positive coefficient of 0.261025 and a p-value less than 0.001, indicating a direct and substantial influence on the adjusted long-short returns.

The model has an Adjusted R-squared value of 0.1288, indicating that approximately 12.88% of the variability in adjusted long-short returns can be explained by this set of predictors. The model's overall significance is confirmed by the F-statistic, with a very small p-value (< 2.2e-16), demonstrating that the variables collectively influence the adjusted long-short returns. In essence, the model reaffirms the significant influence of the 'R_f', 'Volatility', '2-month Forward Yield Curve', and 'SMB' on the adjusted long-short returns.

Incorporating market sentiment into our existing model, we used the VIX - a key sentiment indicator. With VIX data available from 1990 onwards, this analysis worked within a more limited timeframe. Despite the inclusion of VIX-change, our model's predictive power remained consistent, with SMB and volatility maintaining their significance. The inclusion of VIX-change, though not statistically significant, contributed to the model's robustness. While differences were observed in standard error and R-squared values due to the reduced time period, the model's overall statistical significance, as evidenced by the substantial F-statistic, remained intact. Therefore, this model continues to provide valuable insights into the relationship between market factors and adjusted long-short returns, highlighting the importance of volatility and size factor.

6.0 Conclusion

Our extensive research shows a correlation between the yield curve and momentum returns, fundamentally contributing to our understanding of financial market dynamics. Our analysis reveals a notable and statistically significant relationship between the 2-month forward yield curve and momentum returns. This relationship demonstrates a monotonically increasing pattern in momentum returns, highlighting the predictive power of the yield curve. This finding underscores the captivating influence of the yield curve in forecasting and shaping momentum returns. Through our investigative journey, we discover that momentum returns are significantly influenced by the past performance of portfolios, reaffirming the empirical grounding of momentum investment theories.

Intriguingly, our exploration of the temporal dynamics of momentum returns in relation to economic recessions reveals fascinating patterns. Momentum returns appear to mirror the path of the yield curve in the aftermath of a recession, suggesting a strong positive relationship. The most striking finding, however, is the recurrent occurrence of momentum crashes post-recession. While prior studies associate momentum crashes with periods of high market volatility and negative returns, our analysis highlights that these crashes tend to materialize during the recovery phase, a period typically extending 18-24 months post-recession. This novel contribution not only adds to existing knowledge but also provides insight into when momentum crashes are likely to occur following a recession.

We also examine market dynamics leading up to such economic downturns. Notably, our findings reveal a distinct pattern in the yield curve slope, which gradually declines as a recession approaches, reaffirming the link between yield curve inversions and imminent recessions. Similarly, momentum returns exhibit an analogous downward trend in the final months leading up to a recession. However, in the broader 6-12 months preceding a recession, momentum strategies register positive returns. This intricate correlation between momentum returns and the yield curve, both reflecting anticipatory market adjustments to forthcoming recessions, enriches our understanding of market responses to economic downturns.

Our curiosity about the observed downturn in momentum returns 18-24 months post-recession also leads us to delve deeper into three distinctive recessions: the double-dip recession in the early 1980s, the recession following the dot-com bubble burst in the early 2000s, and the Great Recession of 2008. Our analysis of these distinct cases underscores the unique circumstances of each recession and the corresponding impact on momentum returns. Despite their differences, a consistent pattern appears, wherein momentum returns undergo a slump 18–24-month post-recession, potentially signaling broader market recalibration or adjustment.

Transitioning from yield curve dynamics, our research also explores the influence of the VIX on momentum returns. Segmenting our data into four portfolios based on quartiles of VIX values, we find that momentum returns vary significantly across different volatility states. Lower VIX values are associated with negative momentum returns, suggesting momentum strategies tend to underperform in periods of low market volatility. Conversely, higher VIX values shows positive momentum returns, indicating these strategies yield superior returns when market volatility escalates. This finding aligns with existing research, suggesting momentum profits are more pronounced during periods of high market volatility due to slow information diffusion. The interplay between volatility and momentum returns emphasizes the importance of considering market volatility when implementing a momentum-based investment strategy.

Furthermore, our analysis of the impact of portfolio volatility on performance yielded valuable insights. Portfolios with moderate volatility exhibits the highest returns, suggesting an optimal volatility range for maximizing returns. Meanwhile, high volatility portfolios show greater fluctuations in returns and lower risk-adjusted performance, highlighting the significance of the risk-return trade-off in investment portfolios.

Finally, our multi-factor analysis reveals the pivotal roles of various factors in influencing portfolio returns. The volatility, size-based portfolios, and yield curve factors display major influences, while changes in the VIX have less impact on long-short strategy returns. The relationships between these factors and portfolio returns not only enhance our understanding of the intricacies of financial markets but also offer practical insights for investors seeking to optimize their strategies and enhance their portfolio performance.

In sum, our study highlights the complex, multi-dimensional relationship between the yield curve, momentum returns, and various market factors. By establishing the linkages between these variables, we contribute to the rich tapestry of financial market research and provide actionable insights to investors seeking to refine their investment strategies. As we move forward, we hope our findings will serve as a basis for future explorations and stimulate further discussions in this vibrant field of study.

Acknowledgment of Limitations

While this study provides valuable insights into the relationship between the yield curve, volatilities, and momentum returns, it is important to acknowledge certain limitations that may have influenced the findings and should be taken into consideration when interpreting the results.

Firstly, our analysis focuses on a specific time period and a particular set of financial assets. The generalizability of the findings to different time periods, asset classes, or market conditions should be approached with caution. The dynamics between the yield curve, volatilities, and momentum returns may vary under different economic and market contexts, and further research is needed to explore these variations.

Secondly, our study relies on historical data and statistical analyses, which are subject to inherent limitations. While we employ rigorous methodologies and robust statistical models, there may still be factors or variables that were not accounted for in our analysis. Other unobserved variables, market anomalies, or changes in market dynamics could potentially influence the relationship between the variables under investigation.

Thirdly, the nature of our study is observational, and causality cannot be established solely based on the observed relationships. While identifiy associations and patterns between the yield curve, volatilities, and momentum returns, it is crucial to exercise caution in inferring direct causal relationships. Future research could consider experimental or quasi-experimental designs to establish stronger causal links.

Additionally, our study focuses on a specific set of factors and do not consider other potentially relevant variables that could influence momentum returns, such as macroeconomic indicators or geopolitical events. Incorporating a broader range of factors in future studies could provide a more comprehensive understanding of the dynamics at play.

Despite these limitations, this study contributes to the existing body of knowledge on the relationship between the yield curve, volatilities, and momentum returns. By acknowledging these limitations, we highlight the need for further research and encourage scholars to explore these aspects in more detail to enhance our understanding of this complex interplay.

7.0 Literature

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