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UNDERSTANDING THE IMPACT OF KEY DRIVERS ON BETTING AGAINST BETA: AN EMPIRICAL STUDY OF US ECONOMY

Understanding the impact of key drivers on betting against beta: an empirical study of us economy

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ABSTRACT

This research paper investigates the factors that influence betting against beta anomalies, including interest rate (IR), investor sentiments (IS), USA stock trading volume (USV), momentum (MOM), high minus low (HML), small minus big (SMB), and market return in excess of T-bills (MKT). Monthly data is used in the current study for the period of 1987 to 2014 for US firms and data is analyze with the help of OLS regression. We find that HML, IS, and MOM have a significant positive impact on the BAB anomaly, while IR, MKT, and USV have a significant but negative impact. Prior research has not concurrently explored these factors, rendering our study distinct in its comprehensive analysis. The results of this study can be used by a variety of people to make more informed investment decisions and to improve the efficiency of the financial markets.
Keywords: Betting against beta, Anomaly, USA economy, Trading volume, Time series, HML, Investor sentiments.

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UNDERSTANDING THE IMPACT OF KEY DRIVERS ON BETTING AGAINST BETA: AN EMPIRICAL STUDY OF US ECONOMY

Entendendo o impacto dos principais impulsionadores nas apostas contra o beta: um estudo empírico da economia dos EUA

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RESUMO

Este artigo de pesquisa investiga os fatores que influenciam as apostas contra anomalias beta, incluindo taxa de juros (IR), sentimentos dos investidores (IS), volume de negociação de ações dos EUA (USV), momentum (MOM), alto menos baixo (HML), pequeno menos grande (SMB) e retorno de mercado superior às letras do Tesouro (MKT). Os dados mensais são utilizados no presente estudo para o período de 1987 a 2014 para empresas dos EUA e os dados são analisados com a ajuda da regressão OLS. Descobrimos que HML, IS e MOM têm um impacto positivo significativo na anomalia BAB, enquanto IR, MKT e USV têm um impacto significativo, mas negativo. Pesquisas anteriores não exploraram simultaneamente esses fatores, tornando nosso estudo distinto em sua análise abrangente. Os resultados deste estudo podem ser utilizados por diversas pessoas para tomar decisões de investimento mais informadas e para melhorar a eficiência dos mercados financeiros.

Palavras-chave: Apostas contra beta, Anomalia, Economia dos EUA, Volume de negócios, Séries temporais, HML, Sentimentos dos investidores.

INTRODUCTION

Betting against beta is a market anomaly that has been well-documented in academic literature. The basic idea is that low-beta stocks tend to outperform high-beta stocks over time. This is because high-beta stocks are more volatile and therefore riskier, and investors are willing to pay a premium for the additional risk. However, this premium is often too high and low-beta stocks eventually become undervalued. Frazzini and Pedersen (2014) Created the BAB factor, a portfolio that retains low-beta assets while de-leveraging it to a beta of one and shorting high-beta assets. They discover that BAB factors have a positive average return that increases with the difference in beta between securities with high and low betas. There are several factors that may contribute to betting against beta anomaly. One possibility is that constrained investors, such as those with limited borrowing capacity, are more likely to bid up the prices of high-beta stocks. This is because they are unable to take on as much risk as unconstrained investors, and therefore need to earn a higher return on their investments.

Another possibility is that investor sentiment plays a role in betting against beta anomaly. When investor sentiment is positive, investors are more likely to be attracted to high-beta stocks, which are seen as more risky but also more likely to generate high returns. However, when investor sentiment is negative, investors become more risk-averse and are more likely to sell high-beta stocks (Baker and Wurgler, 2006a).One of the prominent concerns in financial literature is how to gauge investor attitude in the stock market(Baker & Wurgler, 2006; Bathia et al., 2016; Canbaş & Kandır, 2009; Kim & Park, 2015; Wang & Chen, 2012). Since behavioral finance emerged as a fresh paradigm to cope with the flaws in investor decision-making and the oddities of the financial market, researchers have been attempting to quantify it. In addition to interest rates, investor sentiment, momentum, HML, and SMB, there are several other factors that may affect betting against beta anomaly. These include the economic cycle, the level of volatility in the market, and the performance of other asset classes.

According to Frazzini and Pedersen (2014) momentum is a measure of the tendency of past winners to continue to win and past losers to continue to lose. Momentum has been shown to be a significant factor in stock returns, and it can also affect betting against beta. When momentum is positive, high-beta stocks tend to outperform low-beta stocks, which can make it more difficult to generate profits from betting against beta. HML and SMB are factors that are used to measure the size and value premiums in the stock market. HML is the difference in returns between a portfolio of small stocks and a portfolio of large stocks, and SMB is the difference in returns between a portfolio of value stocks and a portfolio of growth stocks. Both HML and SMB have been shown to be significant factors in stock returns, and they can also affect betting against beta. Fama and French (1993)introduce the three factors that have become known as the Fama-French factors: market beta (Rm-Rf), size (SMB), and value (HML). They show that these factors can explain a significant portion of the variation in stock returns, and they argue that they are price factors, meaning that investors demand a premium for bearing these risks. According to Frazzini and Pedersen (2014)market return is the overall return of the stock market. Market return is a significant factor in all investment strategies, and it is also a factor in betting against beta. When market returns are high, it is more difficult to generate profits from betting against beta.IR is also a factor that effect betting against beta, according to (Frazzini & Pedersen, 2014) low interest rates make it cheaper for investors to borrow money, which can lead to more risk-taking. This can make high-beta stocks more attractive to investors, as they offer the potential for higher returns with lower downside risk.Santos et al. (2018), when interest rates are low, investors may be willing to take on more risk in search of higher returns. This can lead to higher prices for high-beta stocks, which can reduce the returns from betting against beta".

The traditional approach to investing is to buy stocks that have a high beta, which means that they tend to move up and down in tandem with the market. However, there is a growing body of evidence that suggests that betting against beta, or buying stocks with a low beta, can be a more profitable strategy but the performance of this BAB can be affected by several factors, including interest rates, investor sentiments, momentum, HML, SMB, market return and many other factors for instance Interest rates can affect the performance of betting against beta. When interest rates are low, investors may be more willing to take on more risk, which can lead to higher prices for high-beta stocks(Santos et al., 2018).Investor sentiment can impact betting against beta, with positive sentiment favoring high-beta stocks and potentially reducing returns from this strategy. Conversely, negative sentiment may benefit betting against beta as low-beta stocks become more attractive. Monitoring sentiment and market conditions is essential for successful investment strategies(Frazzini & Pedersen, 2014).When momentum is positive, high-beta stocks tend to outperform low-beta stocks, which can also reduce the returns from betting against beta(Jegadeesh & Titman, 1993).Both HML and SMB have been shown to be significant factors in stock returns, and they can also affect betting against beta.Fama and French (1992) state that market return is a significant factor in all investment strategies, and it is also a factor in betting against beta. When market returns are high, it is more difficult to generate profits from betting against beta(Frazzini & Pedersen, 2014).

This research paper aims to examine the influence of various factors, including interest rates, investor sentiments, USV, momentum, high-minus-low (HML) factor, small-minus-big (SMB) factor, and market return, on the occurrence of betting against beta anomaly within the context of the US economy. By investigating these factors, the study seeks to provide valuable insights for investors seeking to capitalize on betting against beta anomaly. The outcomes of this research will contribute to a deeper understanding of the dynamics underlying such anomaly, empowering investors to make more informed decisions in their pursuit of exploiting these market inefficiencies.

1 LITERATURE REVIEW

1.1 Betting Against Beta: Unveiling Anomalies and Market Variances across Global Portfolios

In the study of(Han, 2019)three portfolios are used in betting against beta (BAB): two cross-sectional portfolios that use stock selection and ranking to take advantage of the beta anomaly, and one time-series portfolio with a dynamic net-long position based on beta parity. The time-series portfolio accounts for the majority of BAB's outstanding performance, whilst the cross-sectional portfolios mostly provide hedging advantages during market downturns. Relatively little turnover occurs in the time-series portfolio. Similar outcomes can be obtained by betting against correlation (BAC), albeit the outperformance of cross-sectional portfolios in BAC is purely due to the association between business size and stock correlation. The performance of BAC declines more than that of BAB when micro-cap stocks are taken out of the equation. In the end, the only reliable source of gains in BA-style strategies is the time-series portfolio. Syrmas (2019)uses a sizable dataset made up of over 1,500,000 stock data observations from the Euro zone, aimed to experimentally analyze this anomaly. Using the betting against beta (BAB) technique, they created 12 portfolios, adhering to the process given by(Frazzini & Pedersen, 2014). Their data shows that BAB portfolios have an average monthly excess return that is positive. They found compelling evidence of beta disequilibrium in the Euro zone. However, because their coefficients were statistically insignificant, they were unable to detect a connection between possible funding shocks and BAB portfolio returns. Their findings imply that the beta anomaly is not limited to a single market and that leverage-unrestricted investors inside the Euro zone can successfully adopt beta arbitrage strategies, producing sizable positive returns. Bali et al. (2014) analyze the impact of lottery demand; the betting against beta phenomena loses its relevance using portfolio analysis and regression analysis. The effect is not explained by other variables like business characteristics, risk metrics, or funding liquidity sensitivity. It should be noted that the betting against beta effect only appears when lottery demand unfairly favors high-beta equities.

Furthermore, the aberrant returns of the betting against beta portfolio and the Frazzini and Pedersen betting against beta factor are satisfactorily explained by their factor models, which also include a lottery-demand component. This suggests that the desire for equities with lottery-like features is what is most to blame for the problem. Rana et al. (2021) determines that whether employing a betting against beta (BAB) strategy results in favorable risk-adjusted returns in the Indian market. Using information from the NSE 500 securities, they built portfolios of low- and high-beta companies to study this. This research shows that the BAB factor produce favorable risk-adjusted returns. This suggests that, in contrast to the expectations of the Capital Asset Pricing Model (CAPM), the securities market line in the Indian market has a flatter slope. Furthermore, this research shows that the Indian market exhibits a volatility anomaly. In particular, they find that holding long positions in low volatility assets and short positions in high volatility securities can result in positive risk-adjusted returns for investors. According to Durham (2016) recent research has emphasized the potency of "low-risk" trading tactics that take advantage of the U.S. Treasury (UST) term structure's negative link between Sharpe ratios (SRs) and maturity. By investigating the betting against beta with government bonds (BAB GOV) approach from several angles, this paper furthers this line of inquiry. By highlighting the conflict between leverage restrictions and low-risk investment, recognizing potential changes in excess returns, and examining the effects of co skew preferences in government bond markets; this study deepens our knowledge of the BAB approach.

Kolokolova and Xu (2022) shows the stochastic dominance (SD) relationship between stocks and the market portfolio can help the betting-against-beta (BAB) investment strategy perform better. The performance and risk measurements of the approach are greatly improved by removing stocks from the long leg that are dominated by the market and vice versa. These enhancements, especially in third-order SD, continue to be resistant to transaction costs and other market circumstances. Sehgal et al. (2022) delves into the betting against beta (BAB) anomaly across major Asian markets spanning from January 1999 to January 2020. The study discovers positive BAB premiums in India, China, and South Korea, while Japan and Indonesia exhibit negative premiums. These variations in BAB premiums are linked to factors such as information uncertainty and market development. The decomposition analysis identifies that betting against correlation drives premiums in India, whereas betting against volatility influences China and South Korea. Furthermore, funding liquidity risk and margin constraints play a role in India and Indonesia. The study concludes that the applicability of the BAB strategy varies across markets, and the drivers of its premiums differ accordingly.

1.2 Exploring CAPM Anomalies: Evidence from Global Markets and Betting Against Beta Strategies

Jensen et al. (1972) Established an adverse deviation in returns for portfolios comprising high-beta stocks within the framework of CAPM. Their study showcases that portfolios composed of high-beta stocks generate reduced returns compared to the CAPM's expectations, whereas portfolios of low-beta stocks achieve elevated returns. This beta anomaly has also been explored in subsequent research by scholars such as (Blume & Friend, 1973; Fama & French, 1992, 1993; Fama & MacBeth, 1973) and (Baker et al., 2011). Pasetti and Montagna (2021) investigate the connection between risk and reward, concentrating on the "Low Risk Effect." They examine the validity of the conventional wisdom that says increased risk entails higher profits. They examine key financial theories, such as Modern Portfolio Theory, CAPM, and Black's model, to investigate this relationship and the effects of behavioral and leverage limitations. To compare the performance of these techniques to a benchmark index, they make some adjustments. Additionally, by detecting periods of low stock correlation and figuring out the strategies sector composition, they try to construct a lucrative approach for the S&P 500. In this study, the link between risk and reward is examined, the BAB and BAC techniques are analyzed and industry-specific performance drivers and correlation dynamics are investigated.

Campbell and Kassa (2022) demonstrate, that the positive anomalous returns observed in the Betting-Against-Beta (BAB) strategy are the result of market segmentation brought on by the costly acquisition of information, as stated by (Merton, 1987). The projected returns and CAPM alphas for the BAB strategy are positive, which is consistent with their predictions. Both negatively across businesses with lower visibility and positively over time based on the beta spread and shadow cost of information of the portfolio characterize these returns as different. These results cannot be explained by alternative factors such as financial illiquidity or a preference for lottery-like stocks. Sørensen (2015) examined the Betting against Beta (BAB) theory using data from national stock indices and US treasury bonds from 8 different nations. The Sharpe ratios and alphas showed a deteriorating trend as the portfolios went from low-beta to high-beta. However, when switching from low-beta to high-beta portfolios, there was an increase in alpha for the US and UK stock indices. Both proposals for the BAB portfolio received support from all 8 nations. The portfolios had favorable abnormal returns and a trend towards higher returns with increasing beta spread. Additional factor returns based on size, book-to-market, and momentum were incorporated in the research and they investigated the effect of stricter portfolio limits on the BAB factor using time series regression. Except for Sweden, Switzerland, and US treasury bonds, the findings were statistically significant for the lagged level of the TED spread in every nation. In the majority of nations, the beta spread coefficient was favorable and statistically significant.

1.3 Investor Sentiment and the Betting against Beta Phenomenon, exploring Connections in Financial Markets

According to Abdollahi et al. (2017) the beta anomaly challenges the traditional Capital Asset Pricing Model (CAPM) by contradicting its prediction of a positive relationship between a stock's beta and its future returns. This discrepancy, known as "betting against beta" (BAB), has sparked debate among researchers. In this study, the authors propose new multi-factor models to better understand BAB, incorporating investor sentiment and utilizing structural equation modeling within a top-down approach. Their findings indicate that investor sentiment plays a significant role in explaining the BAB phenomenon. Hakala (2015) says that Capital Asset Pricing Model (CAPM) suggests a positive relationship between a stock's beta and its future returns. However, this empirical study has shown conflicting results, with low-beta stocks often outperforming high-beta stocks.

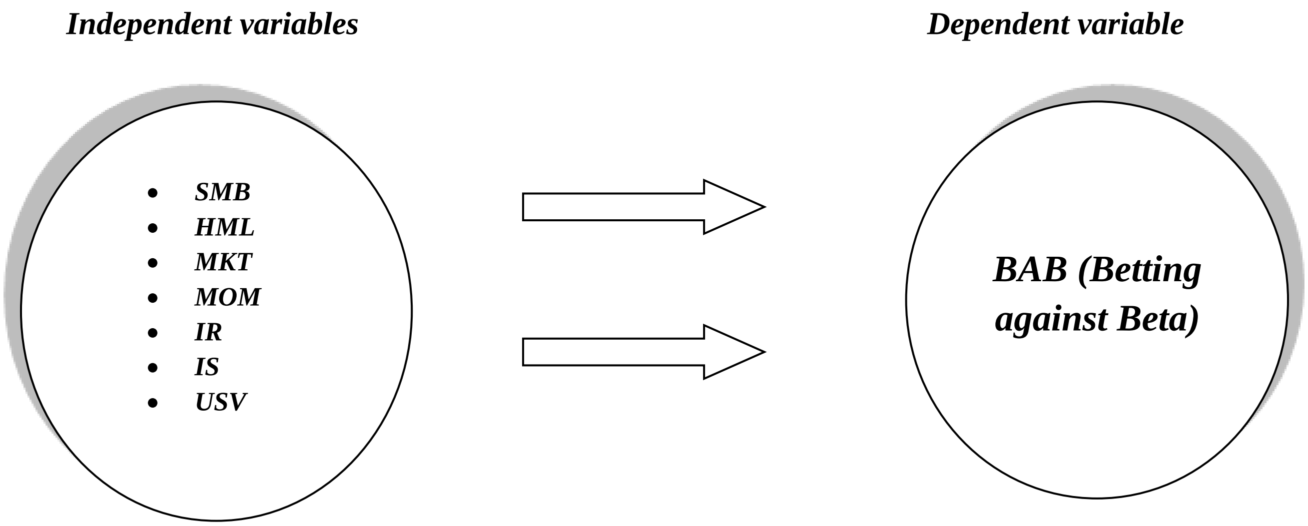
Frazzini and Pedersen (2014) demonstrated that a strategy known as betting against beta (BAB), involving buying low-beta assets and shorting high-beta assets consistently generates positive returns across various markets and asset classes. In this paper, they took a conservative approach to investigate the existence of the betting against beta phenomenon in the stock market. Moreover, they explore whether high-beta stocks possess specific characteristics that make them more susceptible to investor sentiment, which measures the collective mood and trust of individual investors. Ultimately, their research aims to determine either investor sentiment can explain the observed betting against beta phenomenon in the stock market. Gaies et al. (2022) examining the connection between investor sentiment and financial instability in the U.S. financial market. The study employs a bootstrap rolling window subsample Granger causality approach to investigate the dynamics. The findings reveal that during non-crisis periods, bullish sentiment can actually reduce financial instability. Conversely, higher instability is associated with less bullish sentiment, leading to crisis periods. Moreover, bearish sentiment has a positive impact on instability during crises, while bullish sentiment has a negative impact. The study also highlights the relevance of the "betting against beta" strategy, which negatively affects bearish sentiment in both pre- and post-crisis periods.

1.4 Impact of Interest Rate Changes on Low Beta Portfolio Performance, insights from Macroeconomic Factors and Risk Management Strategies

Muijsson et al. (2015) Conducted a study which aims to the understanding of portfolio performance and macroeconomic factors by examining the response of a low beta portfolio to changes in interest rates. The findings have significant implications for fund managers heavily invested in low-risk strategies, particularly concerning potential risks associated with future IR increases. Specifically, the study reveals that low beta funds tend to exhibit better performance during periods of falling interest rates compared to rising interest rates. The analysis focuses on US equity investment using the capital asset pricing model (CAPM). The results suggest that the anomaly can be partially explained by changes in IR direction resulting from macroeconomic events, with varying impacts observed for low and high beta portfolios.

The phenomenon of betting against beta (BAB) anomaly has been the subject of extensive research, with numerous studies exploring the effects of various factors. Nevertheless, this study differentiates itself in two key aspects. Firstly, it adopts an extended time frame, spanning from 1987 to 2014, thereby facilitating more precise and robust findings by encompassing a wider range of market conditions. Secondly, this investigation incorporates an examination of the impact of IR, USV, and IS on BAB anomaly. Notably, prior research has not concurrently explored these factors, rendering our study distinct in its comprehensive analysis. The empirical results obtained from our study reveal the potential significance of these factors in influencing the performance of BAB strategies. Thus, this research contributes to the existing literature by shedding new light on the dynamics of BAB anomaly and their associated determinants.

Figure 1 -Conceptual framework



2 METHODOLOGY

This section contains the technical information of the study.

2.1 Data source

Our study is based on the economy of United States. For our analysis in the current study, we use monthly data that covers the period from 1987 to 2014 and collected all data from different websites. BAB, SMB, HML, and MKT data are collected from Andera Frazzani AQR Capital Management website, MOM data are extracted from Kenneth R. French website, IR data are extracted from FRED's website, IS data are collected from Jeffrey Wurgler's website, and historical USV data are collected from Yahoo Finance's website.

2.2 Methods

We collect all 8 variables data on monthly basic, and we match variables dates with each other by using MS Excel; no specific software is used for matching data because it is available on monthly basic. Then we take that data in E-views (find Correlation, descriptive table, and find VIF for robustness check) and, using Micro-fit to estimate the results of OLS regression. We applied Ordinary Least Squares (OLS) regression to estimate the results for several reasons: OLS assumes a linear relationship between the dependent and independent variables, which is often a reasonable assumption in many economic and financial contexts and OLS also provides straightforward interpretation of coefficients. The estimated coefficients directly indicate the change in the dependent variable associated with a one-unit change in the independent variable, holding other variables constant. Another reason is that OLS estimates become consistent as the sample size increases, means that more the data, means estimates become closer to the true population parameters. OLS estimators are the Best Linear Unbiased Estimators (BLUE) under certain assumptions, meaning they have the smallest variance among linear unbiased estimators.

OLS can also control for potential confounding factors and assess their individual impacts on the dependent variable while controlling for others. One more unique point of OLS is that estimates can be paired with diagnostic tests to assess the validity of assumptions, such as normality of residuals, heteroscedasticity, Multicollinearity, and more.

For the readers' convenience, a detailed description of the variables is present in Table 1.

Table 1 - Detailed description of independent and dependent variables

Name of the variables	Description of variables	Citation	Data Sources
Dependent variables			
BAB(Batting Against Beta)	BAB factor are the portfolio in which we long low beta asset and short high beta assets. In order to construct the BAB factor all securities of a country ranked in ascending order according to their betas and ranked securities are assigned one type of portfolio from 2 portfolios low or high beta portfolio.	(Frazzini & Pedersen, 2014)	Andera Frazzani AQR capital management website
Independent Variables			
SMB(Small minus Big)	The SMB factor measures the excess returns of small-cap stocks over large-cap stocks. The idea behind this factor is that historically, smaller companies have outperformed larger companies in terms of risk-adjusted returns. To construct the SMB factor, French and Fama divide the stock universe into two portfolios: a small-cap portfolio and a large-cap portfolio. The returns of these portfolios are then compared to calculate the SMB factor.	(Frazzini & Pedersen, 2014)	Andera Frazzani AQR capital management website
HML(High Minus Low)	The HML factor, on the other hand, captures the excess returns of high book-to-market (value) stocks over low book-to-market (growth) stocks. The concept here is that value stocks, which have relatively low prices compared to their fundamental value (book value), tend to outperform growth stocks in the long run. To calculate the HML factor, French and Fama divide stocks into two	(Frazzini & Pedersen, 2014)	Andera Frazzani AQR capital management website

	portfolios based on their book-to-market ratios and then compare the returns of these portfolios.		
MKT(MARKET RETURN IN EXCESS OF T- BILLS)	The MKT factor represents the excess return of the overall market (usually represented by a broad market index, such as the S&P 500) over the risk-free rate, which are typically proxies by the return on Treasury bills (T-Bills). T-Bills are short-term government securities considered to have negligible default risk, making them a common benchmark for the risk-free rate. To calculate the MKT factor, the return on T-Bills is subtracted from the return of the market index for a given period. The resulting figure represents the excess return of the market over the risk-free rate. A positive MKT factor indicates that the market outperformed the risk-free rate during that period, while a negative MKT factor suggests underperformance relative to the risk-free rate	(Frazzini & Pedersen, 2014)	Andera Frazzani AQR capital management website
Mom(Momentum)	Mom is equal to the average of the returns on two (large and small) portfolios with high past returns less the average of the returns on two portfolios with poor prior returns. The portfolios are built on a monthly basis. Big signifies a company's market capitalization was higher than the NYSE's median at the end of the preceding month; tiny companies have market capitalizations that are lower. The prior return is calculated using the	(Barroso & Maio, 2016)	Kenneth R. French Website

	months -12 to -2. The companies in the poor past return portfolio are under the 30th percentile on the NYSE. Those in the high portfolio rank higher than the 70th percentile on the NYSE**.**		
IR(Interest rate)	An IR is the cost or price of borrowing money, typically expressed as a percentage of the loan amount or investment. It represents the compensation that a lender or investor receives for lending money or deferring the use of funds. Interest rates are prevalent in various financial transactions, including loans, mortgages, bonds, and savings accounts	(Syrmas, 2019)	Federal reserve economic data (FRED)
IS(Investors sentiments)	Investor sentiment refers to the overall attitude, emotions, and psychology of investors towards the financial markets or specific investment opportunities. It reflects the collective mood or sentiment of market participants, which can influence their decision-making and behavior. And the investor sentiment data includes monthly time-series values of the sentiment index introduced in **(Baker and Wurgler, 2006**). Their sentiment index combines six investor sentiment proxies to create one that captures the effects of all.	(Abdollahi et al., 2017)	Jeffrey Wurgler’s website
USV(USA stock volume)	In finance, USV is a measure of the total number of shares or contracts traded in a particular security or market during a specific time period. It is calculated by adding up	(Frazzini & Pedersen, 2014)	Yahoo Finance

	the daily USVs for each day in the time period. Monthly USV can be a useful tool for investors and traders. It can be used to identify periods of high or low trading activity, which can be a sign of investor interest or lack thereof. Monthly USV can also be used to track the performance of a security or market over time.	

2.3 Model of study

$$\textbf{(BAB)} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} \boldsymbol{smb_t} + \boldsymbol{\beta_2}\textbf{hml}_t + \boldsymbol{\beta_3}\textbf{mkt}_t + \boldsymbol{\beta_4}\textbf{mom}_t + \boldsymbol{\beta_5}\textbf{Ir}_t + \boldsymbol{\beta_6}\textbf{Is}_t + \boldsymbol{\beta_7}\textbf{USV}_t + \mathcal{E}_t \quad \textbf{(1)}$$

Here,
Y= betting against beta
β_0 = refers to each entity's unidentified intercept.
SMB = Small minus big
HML = high minus low
MKT = market return in excess of t-bills
MOM = MOMENTUM factor
IR = IR (IR is macroeconomics variable which we used to test its impact on BAB)
IS = IS (Investor sentiments is basically a behavioral finance variable that we used to test whether investor sentiment impact betting against beta anomaly or not)
USV= USA stock trading volume
Ɛ = refers to the error term

3 RESULTS AND DISCUSSIONS

The findings and their explanations are presented in this section. We are starting with descriptive statistics in Table 2. The mean of the variables Investor sentiments, BAB, SMB, HML, MKT, and MOM, IR, and USV are positive. The median of all the variables is close to the mean, except for the Interest rate and USV. This means that the distribution of most of the variables is symmetric, except for the Interest rate and USV. In this table, all these variables' mean values are smaller as compared to their SD, which shows that all these factors are not under-dispersed. The skewness of IS, SMB, HML, and USV is positive. This means that the distribution of most of the variables is skewed to the right, except for MOM, BAB, Interest rate, and MKT. The kurtosis of all the variables is greater than 3, except for the Interest rate. This means that the distribution of most of the variables is more peaked than the normal distribution, except for the Interest rate. The Jarque-Bera test for normality of all the variables rejects the null hypothesis of normality. This means that the distribution of all the variables is not normally distributed.

Table 2 - Descriptive stats

	IS	BAB	SMB	HML	MKT	MOM	IR	USV
Mean	0.23	0.01	0.00	0.00	0.01	0.56	3.68	36007.02
Median	0.14	0.01	0.00	0.00	0.01	0.61	4.18	23702.25
Maximum	3.08	0.15	0.13	0.27	0.12	18.20	7.00	161843.60
Minimum	-0.87	-0.16	-0.10	-0.18	-0.23	-34.30	0.50	2687.28
Std. Dev.	0.60	0.04	0.03	0.04	0.05	4.72	2.15	35936.16
Skewness	1.47	-0.51	0.36	0.96	-0.99	-1.64	-0.15	1.07
Kurtosis	7.01	6.11	4.79	13.98	5.92	14.95	1.61	3.28
Jarque-Bera	346.20	150.26	52.27	1738.06	174.16	2152.03	28.21	65.67
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	77.83	2.66	0.27	0.56	2.22	187.05	1237.18	12098358.00
Sum Sq. Dev.	121.09	0.53	0.26	0.45	0.69	7466.96	1543.91	433000000000.00
Observations	336.00	336.0	336.00	336.00	336.00	336.00	336.00	336.00

After analyzing the descriptive statistics, we proceed to examine the correlation results presented in Table 3. The findings indicate a weak but positive correlation coefficient of 0.2 between betting against beta (BAB) and investor sentiments. This suggests that when investor sentiment is high, the price of BAB tends to increase, and vice versa. This positive correlation can be attributed to BAB being a small-cap stock that tends to outperform large-cap stocks during periods of elevated investor sentiment. The higher volatility associated with small-cap stocks often attracts investors seeking growth opportunities, influencing the price of BAB.

On the other hand, a negative correlation coefficient of -0.08 is observed between interest rates and BAB. This indicates that as interest rates rise, the price of BAB tends to decline, while a decrease in interest rates corresponds to an increase in the price of BAB. The negative correlation can be explained by two factors. Firstly, rising interest rates result in increased borrowing costs for companies, making investment and expansion more expensive. This scenario often leads to lower stock prices, including BAB. Secondly, BAB, being a low-beta stock, exhibits lower volatility compared to high-beta stocks. Consequently, when interest rates rise, investors tend to adopt a more risk-averse approach, reducing their demand for low-beta stocks like BAB.

The correlation analysis also reveals a negative and moderate correlation coefficient of -0.35 between USV and IS, as well as a weak negative correlation coefficient of -0.11 between USV and BAB. The negative correlation between USV and BAB can be attributed to the inherent lower volatility of BAB as a low-beta stock. When USV is high, indicating increased market activity, the volatility across all stocks, including BAB, tends to rise. This heightened volatility can impact the price of BAB.

Regarding the relationships between small-minus-big (SMB), high-minus-low (HML), market return (MKT), momentum (MOM), and the aforementioned variables, the correlation coefficients reveal weak associations. SMB and IS exhibit a weak negative correlation of -0.03, while SMB and BAB display a weak negative correlation of -0.10. HML and IS demonstrate a weak but positive correlation of 0.07, while HML and BAB exhibit a weak positive correlation of 0.14. The correlation between HML and SMB is weakly negative at -0.08. MKT and IS reveal a weak negative correlation of -0.12, while MKT and BAB display a weak negative correlation of -0.23. MKT and SMB show a weak positive correlation of 0.25, while MKT and HML exhibit a weak negative correlation of -0.01. MOM and IS present a weak positive correlation of 0.10, while MOM and BAB display a weak positive correlation of 0.24. The correlation between MOM and SMB is weakly negative at -0.06, while MOM and HML exhibit a strong negative correlation of -0.70. MOM and MKT reveal a weak negative correlation of -0.19.

Furthermore, the correlation coefficients indicate a weak negative correlation of -0.14 between interest rates and SMB, a weak negative correlation of -0.08 between interest rates and HML, a weak negative correlation of -0.02 between interest rates and MKT, and a weak positive correlation of 0.10 between interest rates and MOM. USV demonstrates a weak positive correlation of 0.04 with SMB, a weak positive correlation of 0.05 with HML, a weak negative correlation of -0.06 with MKT, and a weak negative correlation of -0.15 with MOM.

Table 3 - Correlation results

	IS	BAB	SMB	HML	MKT	MOM	IR	USV
IS	1.00							
BAB	0.21	1.00						
SMB	-0.03	-0.10	1.00					
HML	0.07	0.14	-0.08	1.00				
MKT	-0.12	-0.23	0.25	-0.01	1.00			
MOM	0.10	0.24	-0.06	-0.70	-0.19	1.00		
IR	0.29	-0.08	-0.14	-0.08	-0.02	0.10	1.00	
USV	-0.35	-0.11	0.04	0.05	-0.06	-0.15	-0.67	1.00

After discussing the correlation table, we now turn our attention to the ordinary least squares (OLS) regression results presented in Table 4. The findings reveal significant impacts of HML, IR, IS, MKT, MOM, and USV on betting against beta (BAB) at a 5% level of significance. Regarding HML (High minus Low) a one-unit increase in HML leads to a 0.55654 unit increase in BAB. This positive relationship between BAB and HML in the US economy can be attributed to the fact that both factors may capture the same underlying risk factor. During periods of market volatility, investors tend to favor low-beta stocks, including BAB, as a means to mitigate risk. Consequently: both betting against beta and HML strategies may benefit from heightened market volatility. These findings align with prior studies conducted by (Barroso & Maio, 2016; Lehnert, 2022).In terms of interest rates, a one-unit increase in interest rates results in a 0.00478 unit decrease in BAB. When interest rates rise, BAB tends to underperform, as investors tend to favor stocks with higher betas. The higher potential returns offered by high-beta stocks become more attractive to investors in such an environment. Consequently, betting against beta strategies is likely to face challenges during periods of rising interest rates.

Moving to IS and momentum factor, a one-unit increase in IS and momentum leads to a 0.00733 and 0.00469 unit increase in BAB, respectively, at a 5% level of significance. This positive relationship can be explained by the fact that momentum stocks, typically small-cap stocks, tend to have lower betas than large-cap stocks. Hence: both betting against beta and momentum strategies may capture the same underlying risk factor resulting in a positive correlation. These findings align with studies conducted by(Barroso & Maio, 2016)and (Lehnert, 2022). Additionally, when investor sentiment is positive, investors tend to favor low-beta stocks due to their perceived lower risk. Consequently, during periods of positive investor sentiment, the demand for low-beta stocks such as BAB increases, leading to higher prices and returns. These results are consistent with the study conducted by(Abdollahi et al., 2017).

Examining the relationship between market return (MKT) and USV with BAB, a one-unit increase in MKT and USV leads to a 0.09939 and 0.0000002012 unit decrease in BAB, respectively, at a 5% level of significance. The negative impact of MKT on BAB can be attributed to several factors. First, low-beta stocks tend to be less liquid compared to high-beta stocks, making it more challenging to buy and sell low-beta stocks and profit from betting against beta. Second, low-beta stocks exhibit lower correlation with the overall market. Consequently, during periods of positive market returns, low-beta stocks may not rise as much as other strategies that are more correlated with the market. These findings align with the study conducted by (Lehnert, 2022). As for USV, the negative relation with BAB in the US economy can be attributed to increased liquidity and volatility. Higher USV leads to increased liquidity, making it easier to buy and sell stocks, which reduces the performance differential between low-beta stocks and the overall market. Moreover, increased USV can lead to heightened volatility, resulting in challenges when profiting from betting against beta, as low-beta stocks are more sensitive to changes in volatility. These results align with the findings of (Frazzini & Pedersen, 2014).

The R-squared value indicates that 30% of the changes in BAB can be attributed to the independent variables (HML, IR, IS, MKT, MOM, and USV), while the remaining changes are attributed to error terms. Additionally, the F-statistic shows that the model as a whole is statistically significant with a probability value of 0.000.

Table 4 - Ordinary least square (OLS) Results

Ordinary Least Squares Estimation

Dependent variable is BAB
1987 month01 to 2014 month 12

Independent Variables	Coefficient	Standard Error	T-Ratio[Prob]
HML	0.55654	0.75250	7.3959[0.000]
IR	-0.00478	0.0011914	-3.9689[0.000]
IS	0.00733	0.003380	2.1683[0.031]
MKT	-0.09939	0.043904	-2.2639[0.024]
MOM	0.00469	0.000593	7.9021[0.000]
SMB	-0.033056	0.069714	-0.47416[0.636]
USV	-0.0000002102	0.000000072	-2.8952[0.004]
C	0.028342	0.0068172	4.1575[0.00]

R-Squared= 0.29725
F-Stat. = 19.8200[.000]

Diagnostic Tests

Serial Correlation	14.4415[.273]
Functional Form	0.91289[.339]
Heteroscedasticity	0.26067[.610]

After discussing the OLS results, we proceeded to apply diagnostic tests to assess the reliability of our estimates. Table 5 presents the results of these diagnostic tests, including serial correlation, Heteroskedasticity, and functional form. It is crucial to interpret these diagnostics correctly to ensure the validity of our findings.

Heteroskedasticity refers to the situation where the variance of the error terms in a regression model is not constant. This can arise due to various factors, such as measurement errors in the independent variables or the presence of outliers in the data. Heteroskedasticity can result in inaccurate standard errors and confidence intervals, necessitating testing and appropriate correction.

Serial correlation, on the other hand, pertains to the correlation among the error terms in a regression model over time. It can occur if the independent variables are not accurately measured or if there are unobservable factors influencing the dependent variable across time. Serial correlation can lead to inaccurate standard errors and confidence intervals, necessitating testing and appropriate correction.

Functional form refers to the specification of the relationship between the independent variables and the dependent variable. Accurate specification of the functional form is crucial for obtaining unbiased estimates of the regression coefficients. If the functional form is incorrectly specified, it can introduce bias in the estimated coefficients.

To evaluate the diagnostic test results, we assess the probability values reported in Table 4. And table 5 shows hypothesis of diagnostic test. If the probability value of a diagnostic test is greater than 0.1, we accept the null hypothesis associated with that diagnostic. In our case, all three diagnostics—serial correlation, functional form, and Heteroskedasticity—yield probability values greater than 0.1. Therefore, we accept the null hypothesis that the error term is not serially correlated, the variance of the error term is not heteroskedastic, and the functional form is not incorrectly specified.

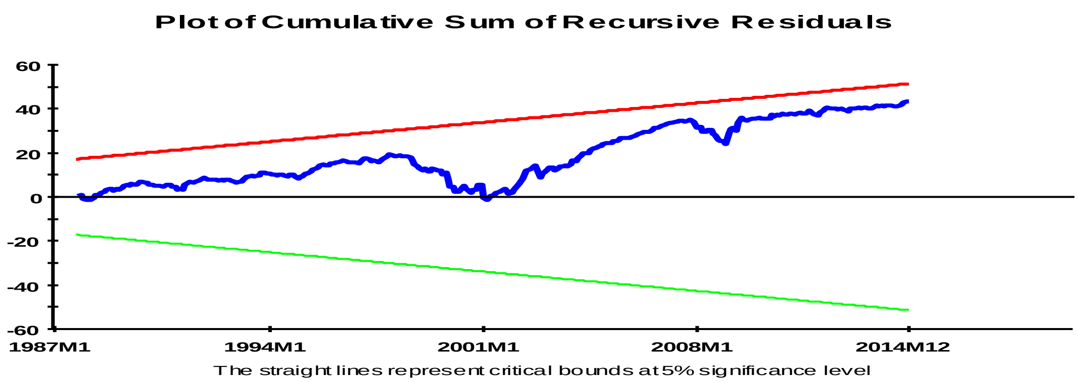
To further examine the stability of the estimated coefficients over time, we utilize a CUSUM graph, presented in Figure 2. The graph demonstrates that the blue line lies within the confidence interval lines, indicating that all estimated coefficients possess a stable mean of error terms. Consequently, we can confidently conclude that our estimated model and results are reliable.

Through rigorous diagnostic testing and graphical analysis, we have established the trustworthiness and validity of our study's estimated model. These findings strengthen the credibility of our research and contribute to the body of knowledge in the field of finance.

Table 5 - Hypothesis for Diagnostics tests

Hypothesis	
<u>Functional test</u>	<u>CUSUM</u>
Ho: functional form is not miss specified	CUSUM tell us about stability of mean of error term if its line is in between confidence interval it means it is stable.
<u>Serial correlation</u>	<u>Heteroskedasticity test</u>
H0: Error term is not serially correlated	Ho: variance of error term is not heteroskedastic.

Figure 2 - CUSUMGraph



3.1 Robustness check

The assumptions of ordinary least squares (OLS) regression have been fulfilled, as confirmed through a robustness check involving various tests: Variance Inflation Factor (VIF), sensitivity analysis, and Generalized Linear Model (GLM) test.

Begin with the VIF results presented in Table 6. The VIF assesses the presence of Multicollinearity among the independent variables. The table provides the VIF values for each independent variable, such as VIF(BAB, investor sentiment) = 1.04, VIF(SMB, investor sentiments) = 1.001, VIF(SMB, BAB) = 1.011, VIF(HML, investor sentiments) = 1.005, VIF(HML, BAB) = 1.02, VIF(HML, SMB) = 1.006, VIF(MKT, investor sentiments) = 1.014, VIF(MKT, BAB) = 1.056, VIF(MKT, SMB) = 1.065, VIF(MKT, HML) = 1.00, VIF(MOM, investor sentiments) = 1.011, VIF(MOM, BAB) = 1.05, VIF(MOM, SMB) = 1.004, VIF(MOM, HML) = 1.957, VIF(MOM, MKT) = 1.039, VIF(interest rate, investor sentiments) = 1.092, VIF(interest rate, BAB) = 1.006, VIF(interest rate, SMB) = 1.020, VIF(interest rate, HML) = 1.007, VIF(interest rate, MKT) = 1.000, VIF(interest rate, MOM) = 1.011, VIF(USV, investor sentiments) = 1.136, VIF(USV, BAB) = 1.012, VIF(USV, SMB) = 1.002, VIF(USV, HML) = 1.002, VIF(USV, MKT) = 1.003, VIF(USV, MOM) = 1.023, VIF(USV, IR) = 1.818.

Advocates of the VIF test argue that when the estimated value of VIF, calculated using the formula [1 / (1 - R-square)], is less than 10, explanatory variables are not significantly related to one another. Hence, it can be concluded that none of the variables (IS, SMB, HML, MOM, IR, and USV) exhibit Multicollinearity issues.

Table 6 - IF (variance inflation Factor) Results

	IS	BAB	SMB	HML	MKT	MOM	IR	USV

IS	-							
BAB	1.047	-						
SMB	1.001	1.011	-					
HML	1.005	1.021	1.006	-				
MKT	1.014	1.056	1.065	1.000	-			
MOM	1.011	1.059	1.004	1.957	1.039	-		
IR	1.092	1.006	1.020	1.007	1.000	1.011	-	
USV	1.136	1.012	1.002	1.002	1.003	1.023	1.818	-

3.2 Sensitivity Analysis

After VIF test now we move forward toward sensitivity analysis which results are present in table 7 in order to conduct sensitivity analysis we reduce our data and deduct 24 months from original data and run OLS from 1987M1 to 2012M12 and we find that HML, IS and MOM, had a significant positive impact on BAB at 5% level of significance while MKT, USV and IR had a significant negative impact on BAB at 5% level of significance so we don't find any significant change in results, these results are matched with the result of table 4 OLS regression results so this sensitivity check is clear.

Table 7 - OLS results

Ordinary Least Squares Estimation			
Dependent variable is BAB 1987 month 01 to 2012 month 12			
Independent Variables	**Coefficient**	**Standard Error**	**T-Ratio[Prob]**
HML	0.56876	0.78729	7.2243[0.000]
IR	-0.00439	0.00128	-3.4063[0.000]
IS	0.00715	0.00349	2.0500[0.041]
MKT	-0.10532	0.04601	-2.2885[0.023]
MOM	0.00475	0.00061	7.6719[0.000]
SMB	-0.01819	0.07390	-0.24619[0.806]
USV	-0.0000002134	0.000000075	-2.8393[0.005]
C	0.026707	0.00731	3.6522[0.00]

After first sensitivity test we also perform second sensitivity analysis test present in table 8 in this test we reduce our data and deduct 36 months from starting data and run OLS from 1990M1 to 2014M12 and we find that HML, IS and MOM, had a significant positive impact on BAB at 5% level of significance while MKT, USV and IR had a significant negative impact on BAB at 5% level of significance so we don't find any significant change in results, these results are matched with the result of table 4 OLS regression results so this sensitivity check is also clear.

Table 8 - OLS result

Ordinary Least Squares Estimation			
Dependent variable is BAB			
1990 month 01 to 2014 month 12			
Independent Variables	**Coefficient**	**Standard Error**	**T-Ratio[Prob]**
HML	0.55859	0.076152	7.3352[0.000]
IR	-0.005062	0.00125	-4.0493[0.000]
IS	0.00622	0.00361	1.7203[0.06]
MKT	-0.17559	0.04755	-3.6920[0.000]
MOM	0.00440	0.00060	7.3344[0.000]
SMB	-0.09008	0.07145	-1.2606[0.208]
USV	-0.0000002343	0.000000071	-3.2632[0.001]
C	0.031232	0.006735	4.6383[0.000]

3.3 GML Test

After Sensitivity analysis now we move forward toward GLM test which results are present in table 9 and we find that HML, IS and MOM, had a significant positive impact on BAB at 5% level of significance while MKT, USV and IR had a significant negative impact on BAB at 5% level of significance so we don't find any significant change in results these results are matched with the result of table 4 OLS regression results so this check is clear.

Table 9 - GLM RESULTS

Generalized linear models			
Dependent variable is BAB			
1987 month 01 to 2014 month 12			
Independent Variables	**Coefficient**	**Standard Error**	**Z P>|z|**
HML	0.55654	0.75250	7.3959[0.000]
IR	-0.00478	0.0011914	-3.9689[0.000]
IS	0.00733	0.003380	2.1683[0.031]
MKT	-0.09939	0.043904	-2.2639[0.024]
MOM	0.00469	0.000593	7.9021[0.000]
SMB	-0.033056	0.069714	-0.47416[0.636]
USV	-0.0000002102	0.000000072	-2.8952[0.004]
C	0.028342	0.0068172	4.1575[0.00]

CONCLUSION

The primary objective of this research paper is to investigate the impact of various factors, including interest rate, investor sentiments, and USA stock trading volume, momentum, high-minus-low (HML) factor, small-minus-big (SMB) factor, and market return, on betting against beta (BAB) anomalies in the US economy. The findings derived from this research are anticipated to provide valuable insights for investors seeking to exploit betting against beta anomaly.

For the analysis in this study, monthly data covering the period from 1987 to 2014 was utilized, with data collected from various sources as previously detailed in the methodology section. The estimation of results was conducted using the ordinary least squares (OLS) regression method. The findings indicate that HML, interest rate, investor sentiments, market return (MKT), momentum (MOM), and USV significantly impact BAB at a 5% level of significance, except for SMB. Following the estimation of the OLS results, diagnostic tests were performed to assess the reliability of the estimates. These tests encompassed serial correlation, functional form, and Heteroskedasticity.

The results revealed that all three diagnostic tests yielded probability values greater than 0.1. As a result, the null hypothesis was accepted, indicating that the error term is not serially correlated, the variance of the error term is not heteroskedastic, and the functional form is not misrepresented.

To further examine the stability of the error terms, the CUSUM test was employed. The CUSUM graph test demonstrated that the blue line lies within the confidence interval lines, signifying stable mean error terms for all estimated coefficients. Additionally, robustness checks were conducted, including the variance inflation factor (VIF) test, sensitivity analysis, and generalized linear model (GLM) test. The VIF test revealed no reported issues of Multicollinearity for investor sentiments, SMB, HML, MOM, interest rate, and USV. Sensitivity analysis demonstrated no significant deviations in the results compared to the OLS model, thereby reinforcing the consistency of the findings. Likewise, the GLM test produced similar results to those of the OLS model.

5.1 Policy Implication

The results of this research paper suggest that the factors HML, investor sentiments, and MOM can be used to identify stocks that are likely to outperform the market over the long term. However, the factors of interest rates, MKT, and USV should be avoided when selecting stocks for betting against the beta strategy. Overall, this study provides valuable insights into betting against the beta anomaly. The findings of this study can be utilized by a diverse range of individuals to make more informed investment decisions and enhance the efficiency of financial markets. An investor who is interested in betting against beta could use the results of this study to identify stocks that have high HML, investor sentiments, and MOM scores. These stocks are more likely to outperform the market over the long term. A financial analyst could use the results of this study to develop an investment strategy that focuses on stocks with high HML, investor sentiment, and MOM scores. This strategy could be used to generate alpha over the long term. A policymaker could use the results of this study to develop policies that promote the efficient functioning of financial markets. For example, policymakers could encourage the disclosure of information about stocks with high HML, investor sentiments, and MOM scores. This information could help investors to make more informed investment decisions.

Future Research

Future research could examine the impact of other factors on the betting against beta (BAB) anomaly. For example, future research could examine the impact of liquidity, dividend yield, and institutional ownership on betting against beta anomalies.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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