Bond Hedge Effectiveness: A Sentiment-Based Regime Approach and its Portfolio Implications*

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Abstract

This paper examines when U.S. Treasury bonds act as effective hedges against stock market risk and how investor sentiment help identify such periods. I introduce a conditional correlation model, where the effectiveness of the bond hedge varies with the correlation between stocks and bonds along with a novel investor sentiment index derived from Seeking Alpha articles for the period 2007 to 2020. Based on this model, I classify the effectiveness of bond hedge into Strong and Weak hedge regimes to construct asset allocation strategies that adjust stock and bond weights accordingly. I find the strategy which allocates entirely to bonds during Weak hedge regimes outperforms a traditional 60/40 benchmark, while the strategy which shifts fully into stocks underperforms. These results show the value of using sentiment-driven regime signals into portfolio management, helping investors to adjust their portfolios under different bond hedge periods.

JEL Classification: G12, G41, D53

Keywords: Investor sentiment; stock-bond correlation; bond hedge regimes; strong hedge regime; weak hedge regime; asset allocation

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1 Introduction

In his seminal research, Markowitz (1952) argues that the optimal portfolio, in terms of risk and returns, can be achieved by allocating 60% to stocks and 40% to bonds. The success of this portfolio composition is driven mainly by the correlation between stocks and bonds, which has been mainly negative over the years. During periods of negative correlation, the bond market works well in diversifying a stock and bond portfolio and reducing the negative effect of dropping stock market on overall portfolio return. However, during times of positive correlation, the diversification benefit of the bond market decays, leading the two assets to move together (Brixton, Brooks, Hecht, Ilmanen, Maloney, and McQuinn, 2023).

Fluctuations in the stock and bond correlation from negative to positive, and vice versa (Fleming, Kirby, and Ostdiek, 2003), are often explained as the result of changes in macroeconomic factors. Campbell and Ammer (1993) argue that positive shifts in the expected inflation have opposite effects on the stock and bond correlation. This view is challenged when investigating the 2007 to 2020 period, for which the expected inflation is moderate and stable [1] while stock and bond returns are negatively correlated with some short periods of positive correlation[2]. The implication is that macroeconomic factors cannot explain solely the fluctuation of the stock and bond correlation.

Considering the limitation of macroeconomic factors in explaining the variation in stock and bond returns correlation, an alternative explanation is offered through investor sentiment, which is closely related to risk aversion. Baker and Wurgler (2007) defines investor sentiment as "the collective mood or belief of market participants about future returns" and Pratt (1964) defines risk aversion as the "investors' preferences for lower risk and stable returns". From the two definitions it can be implied that in periods of low

[1] Figure 1 shows the 10-Year Breakeven Inflation Rate from 2007 to 2020, based on daily data obtained from the Federal Reserve Bank of St. Louis (FRED). Panel A presents the expected inflation, with periods categorized as low (<1.5%), moderate (1.5%-2.25%), and high (>2.25%) based on predefined thresholds. Panel B presents the distribution of these periods by counting the number of days falling into each inflation category

[2] Figure 2 shows the 22-day rolling correlation between daily returns of the S&P 500 and the 10-Year U.S. Treasury Bond from 2007 to 2020. Panel A shows the 22-day rolling correlations, categorized into low (< -0.2), moderate (-0.2 to 0.2), and high (> 0.2) correlation regimes based on predefined thresholds. Panel B presents the distribution of these correlation periods by counting the number of days in each regime.

investor sentiment (high pessimism), investors tend to become more risk-averse, moving away from risky assets like equities, and moving towards safer assets like bonds, even if fundamentals remain unchanged, (Bloom, 2009). However, when market sentiment improves (low pessimism), investors become less risk-averse and move toward risky assets while lowering their exposure to safe assets, (Ben-Rephael, Kandel, and Wohl, 2012). Considering the above, investor sentiment can signal shifts in risk preferences and explain time-varying stock and bond correlation. This explanation agrees with Barberis, Shleifer, and Vishny (1998) and Vayanos and Woolley (2013) who study how investor beliefs affect portfolio decisions beyond fundamentals. The implicit effect of investor sentiment on the stocks and bonds relationship through risk aversion has further implications to the hedge effectiveness of bonds and ultimately to asset allocation. Investor sentiment-defined regimes can be used to identify periods during which bonds can have a strong or weak hedging effectiveness, leading to better asset allocation decisions and higher portfolio performance.

To examine the time-varying relationship between stock and bond returns and identify different bond hedge regimes, this study utilizes a large dataset of social media articles to extract investor sentiment, i.e., beliefs driven by heuristics, rather than grounded in Bayesian rationality (Shleifer, 2000). The social media dataset, includes around 158,000 articles, published daily between 2007 and 2020 on the *Seeking Alpha* platform, commenting on equities, fixed income, commodities and real estate.

As a first step I explore whether variation in the relative level of investor sentiment obtained by social media data is informative about the future stock and bond returns relation. In periods of negative sentiment, investors move to safer assets such as bonds and the correlation between stocks and bonds gets (more) negative. The empirical investigation of this assumption shows a positive (negative) relation between the investor sentiment and the future correlation between stock-bond returns.

Building on this insight, I then turn to the question whether a day's change in investor sentiment is associated with differences in the stock-bond return relations. This analysis looks at the cross-market hedging and relates to flight-to-quality and flight-from-quality along with the improvement or deterioration of investor sentiment. The empirical inves-

tigation of this assumption shows that during times of extremely small or extremely large daily changes of the investor sentiment, the bond returns have the highest values. Especially during times of very large daily changes in investor sentiment, the stock returns become negative.

Finally, motivated by the time-varying nature of stock and bond correlation and the role of investor sentiment in defining bond hedge effectiveness, this study also examines when U.S. Treasury bonds serve as effective diversifiers. More specifically, I examine the comovement of returns by analyzing bond returns, B_t, given stock returns, S_t. My focus lies in exploring how the relationship $E(B_t|S_t)$ evolves in the presence of investor sentiment and recent stock and bond correlation. I argue that investor sentiment exerts a primary influence on stock market returns and a secondary influence on bond market returns.

I introduce a conditional correlation model in which bond returns respond to stock returns based on investor sentiment, which serves as proxy to measure the investor's risk aversion, and the recent stock and bond correlation capturing the state variable. Based on the estimated model, I define two regimes of U.S. Treasury bonds hedge effectiveness, namely, "Strong" hedge regime and "Weak" hedge regime, which are periods where bonds act as strong and weak hedges against risk in the stock market. The resulting classification provides a regime-dependent view of hedge effectiveness, emphasizing the need for asset allocation strategies that adapt to shifting market conditions rather than relying on static correlation assumptions.

An important question this study addresses is what happens during Weak hedge regimes, when bonds do not provide the expected protection against risk in the stock market. These are the moments when diversification breaks down and investors are most exposed. The ability to identify when bonds offer strong or weak protection gives investors a practical tool for improving diversification when it matters most. This study contributes to asset allocation literature by showing that, even simple strategies informed by conditional hedge signals, can outperform traditional strategies, especially during periods where bonds lose their protective ability. Ultimately, this research provides a new perspective on how investor sentiment can add value to portfolio management.

The results indicate that bonds tend to hedge stocks more effectively when investor sentiment and recent stock bond correlation move in the same direction. In this case, the conditional beta becomes more negative, meaning that bonds are more likely to offset stock losses. This typically occurs either during calm periods where the investor sentiment is low and the stock - bond correlation is negative or during stress periods where the investor sentiment is high and the stock bond correlation is positive. The results show the importance of understanding how investor sentiment and realized stock and bond returns correlation jointly affect the diversification. As such, investors who incorporate signals from both sentiment and stock-bond co-movements can better anticipate changes in how well bonds hedge stock market risk and adjust their portfolios to stay better protected.

The results also show that the regime-based rebalancing approach, where asset allocation adjusts in response to shifts in bond hedge effectiveness, can significantly improve portfolio performance. Specifically, a strategy, which shifts fully into bonds during Weak hedge regimes and returns to a balanced portfolio during Strong hedge regimes, delivers the highest return and lowest risk among all strategies. This highlights the importance of moving to safe assets even when diversification breaks down. In contrast, a strategy, which allocates fully to stocks under Weak hedge regimes, underperforms due to high exposure to stock market risk. The traditional 60/40 strategy shows moderate performance and illustrates that while static diversification can be effective, it fails to adapt to changing market conditions. Overall, these results highlight the practical benefits of using investor sentiment and co-movement signals to guide rebalancing decisions.

The contribution of this paper is threefold. First, I link investor sentiment, measured using textual data from social media articles, with the stock and bond returns correlation, to explain how U.S. Treasury bonds co-move with stocks. Second, I leverage this relationship to classify distinct bond hedge regimes, distinguishing between periods when bonds act as strong and weak hedges. Third, I test different asset allocation strategies based on these identified regimes, assessing their performance especially during weak bond hedge periods.

My paper contributes to the growing literature on the role of investor sentiment in explaining the time-varying relationship between stock and bond returns. Prior studies

such as Baker and Wurgler (2012), Bethke, Gehde-Trapp, and Kempf (2017), Fang, Yu, and Huang (2018), Xing, Cambria, and Welsch (2018) and Alomari, Razzaq, El-Nader, and Alkhataybeh (2021) examine how shifts in sentiment affect stock-bond comovement. Similarly, Xing, Cambria, and Welsch (2018) construct a sentiment index from StockTwits data and apply it within a portfolio allocation framework. Beyond stock-bond correlation, other studies such as Barberis, Shleifer, and Wurgler (2005), and Kumar and Lee (2006) explore how investor sentiment contributes to comovement within the stock market itself.

This study also contributes to the vast literature on the analysis of the stock and bond returns correlation. Gulko (2002) examines the "decoupling" of stocks and bonds during crises and highlights the importance of bond markets during stock markets crashes. In the existing literature there are studies that examine the correlation of the stock and bond returns through the lenses of fundamentals, e.g., Campbell and Ammer (1993), Ilmanen (2003), J. Yang, Y. Zhou, and Wang (2009), Baele, Bekaert, and Inghelbrecht (2010), Duffee (2023) and Brixton, Brooks, Hecht, Ilmanen, Maloney, and McQuinn (2023). The theory behind these studies is that macroeconomic factors such as expected inflation, economic growth and real interest rates affect the stock and bond returns in some way. Finally, studies such as Connolly, Stivers, and Sun (2005), Connolly, Stivers, and Sun (2007), Bansal, Connolly, and Stivers (2014), Chiang, J. Li, and S.-Y. Yang (2015), Sakemoto (2018) adopt a different approach and look into the stock implied volatility to explain the time-varying correlation.

The rest of the study proceeds as follows. Section 2 provides a description of the data used in this study. Section 3 examines how stock and bond return correlation varies with investor sentiment. Section 4 introduces the concept of conditional beta, and how it quantifies the conditional relationship of stock returns to bond returns given the investor sentiment and recent correlation of the returns. This section also introduces and defines the different bond hedge regimes. Section 5 uses the concept of conditional beta to forecast the bond hedge regimes. Section 6 concludes.

2 Data

This study uses daily U.S. stock and bond data and a large dataset of articles from *Seeking Alpha*, over the 2007 to 2020 period. This period, covers years of rapid growth of market-focused social media platforms, such as StockTwits and Reddit, and captures volatile periods such as the Great Financial Crisis (GFC) and COVID-19 pandemic.

2.1 Market Data

I use the S&P 500 market composite index to capture the general trend of the U.S. stock market. I retrieve the daily historical data of the S&P 500 index through Bloomberg, and then calculate daily stock returns based on its closing prices.

For daily bond returns, similar to Connolly, Stivers, and Sun (2005), I use the market yields of U.S. Treasury securities at 10-year constant maturity[3]. The calculation of daily bond returns requires to calculate convexity and duration, which are then combined with observed Treasury yields to derive the implied daily returns (Tuckman and Serrat (2011), Swinkels (2019)).

2.2 Investor Sentiment Index

For the Investor Sentiment Index I retrieve from *Seeking Alpha* over 158,000 articles commenting on specific asset classes, like *Equities*, *Commodities*, *Forex* and *Real Estate*. Table A1 shows that most of the *Seeking Alpha* data set focuses on the stock market, while the rest of the other markets are covered fairly equally in the remaining sections. To build the investor sentiment index, I use the framework as in Lachana and Schröder (2025) by adopting the Loughran and McDonald (2011) lexicon, based on which I identify negative and positive words within the *Seeking Alpha* articles[4]. As part of the sentiment index construction, I also adjust the publication time similar to Garcia (2013), making

[3]Board of Governors of the Federal Reserve System (US), Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis [DGS10], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DGS10, July 19, 2025.

[4]Figure 3 presents the most frequent positive and negative words that appear in the *Seeking Alpha* dataset. Negative words such as volatility, crisis and decline are very common, while strong, gain and opportunity are examples of the most common positive words

sure the investor sentiment will take into account articles published outside the tradings hours.[5]. *Seeking Alpha* has been used extensively in research studies when looking to predict stock returns Chen, De, Hu, and Hwang (2014), J. L. Campbell, DeAngelis, and Moon (2019), and Ding, H. Zhou, and Y. Li (2020).

The summary statistics of the calculated investor sentiment and the daily stock and bond returns are reported in Table 1. Panel A reports the summary statistics, while Panel B presents the correlations for investor sentiment and market indices. Stock market has the highest mean average return and standard deviation (20.59% annualized). Bond market looks more stable, with a lower daily standard deviation (7.8% annualized) but lower average daily return. For both markets, the kurtosis is far above the 3 benchmark of the normal distribution, indicating fat tails and a sharper peak, that is, both markets have higher probability of extreme values. Return distributions are negatively skewed for the stocks, implying frequent small gains and a few large losses, while the bond returns are positively skewed. The stock and bond markets show high negative correlation, around -0.42, while the investor sentiment is negatively (positively) correlated to the stock (bond) returns.

3 Investor sentiment and stock-bond correlation

This section is a preliminary analysis on how stock-bond returns vary with investor sentiment. The relation between investor sentiment level and subsequent short-term stock-bond comovements is investigated, that is, whether variation in the relative level of investor sentiment is informative about future stock-bond return relations. I also investigate how stock-bond comovements vary with the contemporaneous change in investor sentiment, i.e., whether a day's change in investor sentiment is associated with differences in the stock-bond returns. This section derives its ideas from Connolly, Stivers, and Sun (2005) who look in the relationship between stock-bond comovement and VIX.

Table 2 reports on the distribution of forward-looking correlations (using daily returns over days t to $t + 21$) following a given investor sentiment value at the end of day $t - 1$.

[5]More information about the construction and development of the index, along with summary statistics can be found in the Appendix.

Positive (negative) values of the investor sentiment indicate high pessimism (improved) mood in the market, as reflected on the *Seeking Alpha* articles. Overall the mean of the 22-day trading correlations is -0.475. As the investor sentiment gets more pessimistic, the correlation decreases from -0.495 to -0.540. When investor sentiment is less than -0.60, i.e., tone in the social media becomes more positive, then the correlation coefficient is -0.411 which is less than the overall population correlation coefficient. This can be explained intuitively: negative investor sentiment signals to a higher negative correlation for the stock-bond relation, driven by investors who probably rush to hedge against negative returns in the stock markets and indicate that bonds can be a good hedge against negative stock returns. As the investors unload stocks from their portfolio that leads to falling stock prices, on the same time they add more bonds leading to higher returns.

I also explore whether bond and stock returns are related to contemporaneous changes in investor sentiment. To perform this analysis, I sort daily observations on the day's change in the investor sentiment and then calculate the subsample statistics for the different change in sentiment groupings. Table 3 looks into stock and bond returns for daily changes of the investor sentiment. Bond returns are the highest during days of big negative or positive daily changes, that is on the lower and upper 5% percentile the average daily bond return is 0.049 and 0.066 respectively. In between, the average bond returns are substantially lower. During times of negative changes on the investor sentiment the stock market returns are the highest, i.e., 0.064. However, during times of high positive changes on the investor sentiment, i.e., market sentiment becomes negative, the stock returns become negative. This can be explained intuitively: during times of negative sentiment in the market as captured in the social media posts, the investors become risk-averse and start unloading risky assets like stocks while at the same time move capital to safe assets like bonds. In the 95th-100th percentile, the stocks have a negative return of -0.040 and the bonds have the highest daily return of 0.066.

To conclude, investor sentiment provides insights for the dynamics of the stock-bond comovements. When market pessimism increases, subsequent stock-bond correlations decrease indicating a negative relationship between investor sentiment and stock-bond correlations. Moreover, positive and negative high daily changes of investor sentiment

relate to low and high returns of the stock market respectively. All these insights could be tested quantitatively through a linear regression model, which is the topic of the next section.

4 Bond Returns and Conditional *Beta*

In this section, I investigate the comovements of returns by analysing the conditional distribution of bond returns B_t, given stock returns S_t. Specifically, I look on how the $E(B_t|S_t)$ relation might vary with the lagged investor sentiment and the lagged stock-bond correlation. To capture these conditional effects, the following regression model is estimated

$$B_t = \gamma + (\beta_1 + \beta_2 P_{t-1} + \beta_3 \rho^{SB}_{t-22} + \beta_4 P_{t-1}\rho^{SB}_{t-22})S_t + \omega B_{t-1} + \epsilon_t \tag{1}$$

$$\hat{\beta}_t = \hat{\beta}_1 + \hat{\beta}_2 P_{t-1} + \hat{\beta}_3 \rho^{SB}_{t-22} + \hat{\beta}_4 P_{t-1}\rho^{SB}_{t-22} \tag{2}$$

where B_t and S_t are the daily 10-year T-bond and S&P 500 returns respectively; P_{t-1} is the investor sentiment index based on *Seeking Alpha* articles in period $t-1$; ρ^{SB}_{t-22} is the 22-days rolling stock - bond correlation in period $t-22$; B_{t-1} is the bond returns in period $t-1$; ϵ_t is the residual and γ, ω and βs are the coefficients of the regression model. Equation 2 shows the conditional relationship between bond and stock returns, and represents the aggregate effect of stock returns to bond returns, when taking into consideration the lagged investor sentiment and lagged correlation of the two assets. Similarly to Xing, Cambria, and Welsch (2018), I view the sentiment, captured in the *Seeking Alpha* articles, as reflecting the mood of the stock market which I then assume to have an effect on the bond market. In line with Connolly, Stivers, and Sun (2005), I also consider the recent bonds-stocks correlation as potential explanatory factor of the two-assets comovements. Moreover, to ensure that the investor sentiment and correlation

effects are not driven by short-term autocorrelation (Lo and MacKinlay, 1990), the model also includes the lagged bond returns as control variable. Finally, prior to the regression analysis, I normalize the investor sentiment index to have zero mean and unit variance allowing for an easier interpretation of the coefficients in terms of one standard deviation changes to investor sentiment.

Column 1 of Table 4 reports on the coefficients of model 1. The relationship between stock and bond returns is negative, based on β_1 and has the largest impact, implying that when stocks drop, bond returns tend to increase (and vice-versa), consistent with the flight-to-quality (flight-to-risk) behavior. The interaction term between the investor sentiment and stock returns is negative and statistically significant at the 5% level. This term implies that investor sentiment acts as a multiplier of the negative stock market effect to the bond markets, that is for periods of high pessimism and falling stock prices, the bond returns will increase more, i.e., the combined effect of the increasing pessimism and falling stock returns has a positive effect on bond returns. Moreover, the interaction term between lagged investor sentiment, lagged correlation and stock returns is negative and statistically significant. That implies, when both investor sentiment and correlation have the same sign (positive or negative) bond returns respond oppositely to stocks. The lagged bond returns are not statistically significant, indicating no autocorrelation effect for the period I explore.

For robustness, I also evaluate the conditional relationship $E(B_t|S_t)$ without controlling for investor sentiment.

$$B_t = \gamma + (\beta_1 + \beta_3 \rho^{SB}_{t-22})S_t + \omega B_{t-1} + \epsilon_t \tag{3}$$

Column 2 of Table 4 presents the results of not including the investor sentiment in the model. The effect of stock market movements on bond returns increases from -0.15 to -0.17, while the interaction term of lagged correlation and stock returns remains not statistically significant. Comparison of two columns of Table 4 suggests that incorporating investor sentiment marginally improves the explanatory power of the model, as adjusted

R^2 rises from 0.176 to 0.18.

These results indicate that bonds-stocks relationship is not static and can be seen as time-evolving, captured through *conditional beta*, a measure of the time - varying sensitivity of bond returns to movements in the stock market, conditional on the investor sentiment and past correlation. Rather than assuming the stock-bond relationship as constant, conditional beta reflects how this sensitivity changes depending on levels of the investor sentiment and the recent correlation between stock and bond returns. Consequently, conditional beta can be dynamically calculated using realized values of investor sentiment and historical stock-bond correlation, allowing for time-specific estimates of bond-stock sensitivity. This framework, enables to track bond return sensitivity to equity market movements over time, helping to identify when bonds serve as stronger or weaker hedges and differentiate between different regimes.

4.1 Bond Hedge Regimes

To test how much of the bond market movements with regards to stock market movements can be seen through the lenses of a state-dependent framework, I use the calculated conditional beta, based on model 2 and assign distinct bond hedge regimes. By splitting the sample period into bond hedge regimes, I can test when bond market acts as an effective hedge, reducing the effect of falling stock prices and when its hedging effectiveness decays.

Periods for which the calculated conditional beta is less than the 2007-2020 sample median are flagged as Strong hedge regimes, implying an enhanced negative sensitivity of bond markets to stock market movements. Periods for which the calculated conditional beta is greater or equal than the sample median are categorised as Weak hedge regimes, suggesting a weakened hedge effectiveness of bond markets to stock markets.

$$\text{Bond Hedge Regime}_t = \begin{cases} \text{Strong Hedge Regime} & \text{if } \beta_t < \text{median}(\beta_t) \\ \text{Weak Hedge Regime} & \text{if } \beta_t \geq \text{median}(\beta_t) \end{cases}$$

This classification rule assumes the calculated conditional beta encapsulates the varying stock-bond relationship. By defining hedge regimes based on the median, the analysis avoids imposing arbitrary cutoffs and maintains a balanced classification across time. Figure 4 depicts the conditional beta time-series along with the hedge regime switching patterns. Periods of heightened market stress such as 2008 (peak of Global Financial Crisis), 2011 (start of European Debt Sovereign crisis) and 2020 (start of COVID pandemic) are categorised as Strong hedge regimes. All three crises are characterized by elevated market pessimism, negative stock and bond correlation, and bond markets acting as a safe haven asset. Moreover, periods flagged as Weak hedge regimes appear when bond-stock correlation is positive or low and investor sentiment is relatively stable. For these periods, the hedge effectiveness of bond market is weakened providing limited diversification benefits.

To assess how the two assets behave under each regime, I calculate the annualized returns and volatility of stocks and bonds within each regime. Table 5 presents annualized return and volatility of stocks and bonds under strong and Weak hedge regime. Stock performance differs significantly between the two regimes. In the Strong hedge regime, stocks have an annualized return of 22.10%, while in the Weak hedge regime, they have negative annual returns of -5.22%. Regarding the stock volatility, stock returns are less volatile in the Strong hedge regime, with an annualized standard deviation of 12.86%, compared to 18.77% in the Weak hedge regime. Bond performance between the two regimes is also different but not substantial, as in the case of stocks, with annualized bond returns being 5% and 4% during the strong and weak regimes respectively. Bond markets are stable between the two regimes, with annualized standard deviations being 6.68% and 7.8% between strong and weak regimes respectively. Overall, stock returns and risk shift significantly depending on the realized hedge regime.

This regime-based approach highlights the benefit of using investor sentiment when evaluating the hedging effectiveness of bonds, and agrees with Xing, Cambria, and Welsch (2018) who argue about the use of investor sentiment in asset allocation. Assuming a static stock-bond relationship could underestimate risk. Adopting the conditional beta, in asset allocation context, offers a dynamic framework for switching between assets, based on

market changes.

4.2 Dynamic Portfolio Strategies

Leveraging the conditional beta to update the portfolio composition in response to changing market conditions, agrees with the concept of dynamic asset allocation as discussed on Merton (1971), J. Y. Campbell and Viceira (1999), and Ang and Bekaert (2004).

To test the benefit of adopting the conditional beta framework in the asset allocation context, I consider a hypothetical portfolio consisted of stocks and bonds. As part of this exercise, I convert stock and bond returns from daily to monthly frequency, and I also define the monthly hedge regime as the one appearing more frequently among the daily data. I then construct eleven versions of the stock-bond portfolio, with varying weights, and compute for every version and every hedge regime the corresponding annualised Sharpe ratio, reported on Figure 5. For the Strong hedge regime, the highest Sharpe ratio occurs when 40% of the portfolio is allocated to stocks and the 60% to bonds. Past that portfolio composition, Sharpe ratio declines reaching the lowest point when portfolio is fully invested to bonds. In the Weak hedge regime, Sharpe ratio is consistently lower vis-á-vis the Strong hedge regime, occasionally turning negative, indicating returns below the risk-free rate and a weakened hedge effectivenss of the bond market. The results indicate that achieving optimal risk-adjusted returns in a stock-bond portfolio, investors have to continuously monitor the market and identify any regime changes, pointing to rebalancing the portfolio accordingly and moving between stocks and bonds.

After establishing the benefit of using the conditional beta concept within the asset allocation context, I explore how investors can exploit further this approach. During Strong hedge regimes, the optimal portfolio composition requires 60% of the available capital to be allocated to bonds and the remaining to stocks. This portfolio mix does not work well under the Weak hedge regime, raising the question on what the allocation mix should be when bond lose their hedging effectiveness. To test this question, I create and evaluate the below dynamic allocation strategies, where portfolio weights depend on the identified regime at period t:

$$(w_t^{\text{stock}}, w_t^{\text{bond}}) = \begin{cases} (40\%, 60\%), & \text{if Regime}_t = \text{Strong Hedge Regime} \\ (0\%, 100\%), & \text{if Regime}_t = \text{Weak Hedge Regime} \end{cases} \tag{4}$$

$$(w_t^{\text{stock}}, w_t^{\text{bond}}) = \begin{cases} (40\%, 60\%), & \text{if Regime}_t = \text{Strong Hedge Regime} \\ (100\%, 0\%), & \text{if Regime}_t = \text{Weak Hedge Regime} \end{cases} \tag{5}$$

$$(w_t^{\text{stock}}, w_t^{\text{bond}}) = (60\%, 40\%) \quad \forall t \tag{6}$$

Strategy 4 and strategy 5 work differently under the Weak hedge regime. Specifically, 4 is considered more conservative as it moves all available capital to bonds during Weak hedge regime, while strategy 5 is riskier as it moves all available capital to stocks during Weak hedge regime. I compare the two strategies against the 60%-40% baseline stock-bond portfolio, testing how much the portfolio performance can be improved when adopting a dynamic asset allocation approach.

Table 6 reports returns and risk metrics for all three strategies. Strategy 1, the conservative strategy, which shifts all available capital to bonds under the weak regime, outperforms Strategy 2, the risky strategy, which allocates all available capital to equities for the Weak hedge regime, and the 60%-40% baseline strategy. The risky strategy, suffers the most, and performs poorly compared to the other two strategies. The 60%-40% baseline strategy performs worse than the conservative strategy but better than the risky strategy, providing a stable alternative to the risky strategy. Moreover, Panel A of Figure 6 depicts the cumulative returns of the three strategies, confirming the superiority of strategy 1 against the other two strategies.

To conclude, the results suggest that adjusting portfolio allocation based on bond hedge regimes can significantly improve risk-adjusted performance. Strategy 1, which

dynamically adjusts allocations based on bond regime shifts, consistently outperforms both the static 60% stocks - 40% bonds benchmark and the more aggressive Strategy 2. This is an indication of the benefit of adopting a dynamic asset allocation framework, based on the hedging effectiveness of bond markets. Portfolio risk and return can be managed more efficiently when thinking in terms of regime-aware strategies. Investor sentiment plays a significant role in this framework, due to its use in calculating the conditional beta, used to define hedge regimes.

5 Predictive Power of the Conditional *Beta*

As previously discussed, while bonds are traditionally viewed as safe haven assets, their hedging effectiveness is not constant, but varies over time with investor sentiment and co-movement between stocks and bonds. Understanding when and for how long bonds serve as effective hedges against stock market movements, are important questions in asset allocation. These questions implicitly raise the issue of whether the hedging effectiveness of bonds is persistent over time. Financial markets regimes are often persistent, meaning the conditions that define them tend to continue over time (Hamilton (1989), Ang and Timmermann (2012)).

In this section, I test whether bond hedge regimes, as identified by the conditional beta, exhibit persistence and whether the lagged conditional beta contains forward-looking information content. That is, forecasting the hedge regime at period t, using the calculated values of conditional beta at period $t-1$ will allow investors to shift allocations across asset classes in advance, thereby enhancing portfolio performance. More precisely, to forecast bond hedge regimes, I employ a Linear Probability Model (LPM) using the lagged conditional beta as the sole explanatory variable. The target variable is represented as a binary variable of the bond hedge regime at time t, denoted R_t, which equals 1 when the conditional beta falls below the sample median, indicating a Strong hedge regime, and 0 otherwise (Weak hedge regime). Formally, the regime variable is defined as:

$$R_t = \begin{cases} 1 & \text{if } \beta_t < \text{median}(\beta_t), \\ 0 & \text{otherwise} \end{cases}$$

The forecasting model is specified as a linear probability regression of the form:

$$R_t = \alpha + \delta\, \beta_{t-1} + \varepsilon_t \tag{7}$$

where R_t is the predicted probability of being in a Strong hedge regime at time t, based on the one-day lagged conditional beta β_{t-1}. To estimate model 7 I use a 252-day rolling window. At period t, the regression is fitted using the most recent 252 observations from $t-252$ to $t-1$. The fitted value from the Linear Probability Model is calculated as:

$$\hat{R}_t = \hat{\alpha} + \hat{\delta}\, \beta_{t-1} \tag{8}$$

The value $\hat{R}_t$ is interpreted as the predicted probability that the bond market will be in a Strong hedge regime on day t. To convert this continuous forecast into a binary classification, a threshold rule is applied:

$$\hat{R}_t = \begin{cases} 1 & \text{if } \hat{R}_t \geq 0.5 \quad \text{Predicted Strong Hedge Regime} \\ 0 & \text{otherwise} \quad \text{Predicted Weak Hedge Regime} \end{cases}$$

Although binary classification tasks are usually modeled with the help of methods such as logistic regression, classification trees etc., I adopt the Linear Probability Model for its simplicity and interpretability. Importantly, the objective of this paper is not to model precise probabilities, but rather to assess whether the conditional beta at time $t-1$ contains predictive information about future bond hedge regimes. In this context, the fact that predicted values may fall outside the $[0, 1]$ is not a concern. (Angrist and Pischke

(2009), J. Y. Campbell and Thompson (2008)).

The results show that the conditional beta contains predictive value in forecasting bond hedge regimes. The model delivers an out-of-sample R^2 of 28.20% while Figure 7 presents the rolling R^2 over time, revealing a meaningful degree of explanatory power for a univariate specification. These findings suggest that the conditional beta offers valuable forward-looking information about bond hedge regime shifts.

I then use the predicted output $\hat{R^2}$ to re-run the 4.2 process with the predicted bond hedge regimes. Panel B of Figure 6 shows the cumulative returns of the three strategies, as defined from the predicted bond hedge regimes. Strategy 1 outperforms both Strategy 2 and the Benchmark Strategy, suggesting that the predicted regimes effectively capture valuable signals for asset allocation. In contrast, Strategy 2 performs worst, highlighting the importance of adjusting allocations under different bond hedge regimes. Moreover, column 2 of Table 6 summarizes a performance comparison of the three strategies based on the predicted regimes. Strategy 1 achieves the highest annualized return (8.38%) and the highest Sharpe ratio (1.02), indicating high risk-adjusted returns. Additionally, Strategy 1 exhibits the lowest maximum drawdown (-11.12%).

Overall, these results highlight the value of regime-aware dynamic asset allocation. The predictive model enables timely shifts in portfolio composition that improve risk-adjusted returns and reduce downside exposure. Moreover, these results suggest that even simple predictive signals can offer significant improvement over passive benchmarks.

5.1 Robustness

In this subsection, I run robustness tests to assess the predictive power of conditional beta at period $t-1$ and I use a decision tree as an alternative to model 7. Decision trees are a non-parametric approach, making no assumptions for the underlying population and have been used extensively to binary classification problems (Breiman, Friedman, Olshen, and Stone, 1984; Cong, Feng, He, and Xe, 2025).

It is common practice to split the dataset to training and testing samples. Training sample, which is usually 70% of the overall dataset, is used to train the decision tree and then the testing part, the remaining 30%, is used to assess the performance of the

trained classifier. Moreover, decision trees require to set its learning parameters such as maximum depth and minimum sample leaf. I use a grid search approach with time-series cross-validation on the training set to come up with the optimal values of maximum depth and minimum sample leaf. I finally assess the performance of the trained decision tree on the test sample by reporting on the confusion matrix, the receiver operating characteristic (ROC) curve and the area under the surve (AUC).

Table 7 reports the output of the decision tree for the testing sample. The model is highly accurate for both classes, having 82% accuracy and also manages to be highly accurate in terms of positive cases, having a precision of 84%. An additional performance test appears on Figure 8 showing the ROC, which is substantially above the naive benchmark (represented by the dashed diagonal line). Overall, the trained decision tree performs very well in terms of accuracy, precision and any other relevant metric within the testing sample.

6 Conclusions

This paper studies daily stock and bond returns from 2007 to 2020 and examines whether an investor sentiment based on a large dataset of social media data can be linked to variations in the stock and bond return relations. The analysis shows that in periods of negative sentiment, the correlation between stocks and bonds becomes more negative, which is consistent with the idea the investors shift assets in their portfolio. Also, during times of negative sentiment, correlation between risky assets increases, indicating that these assets are exposed to common risk under stress.

An important contribution of this paper is to examine when U.S. Treasury bonds act as effective hedges against stock market risk and how investor sentiment can help identify such periods. I introduce a conditional correlation model that incorporates investor sentiment and recent stock and bond returns correlation. The analysis reveals a time-varying pattern in bond hedge effectiveness that can be classified into Strong and Weak hedge regimes. These regimes can be used as a practical tool for dynamic asset allocation. Three strategies were tested, and the strategy which allocates entirely to bonds during Weak

hedge regimes outperforms the others in terms of returns and risk-adjusted performance.

The key insight of this study is the nature of the conditional beta itself. The interaction term between investor sentiment and recent stock and bond returns correlation plays an important role in determining the bond hedge regimes. This finding supports the notion that increased market pessimism can enhance the demand for "safe heavens" during periods of market stress, thereby, strenghthening the negative co-movement with stocks. Conversely, when bonds and stocks move in the opposite direction (e.g. high correlation and low sentiment or vice versa), bonds lose their effectiveness as hedges. Overall, the results show that investor sentiment can serve as a proxy to measure the investors' risk aversion, which then can be used to inform investment allocation decisions between stock and bonds.

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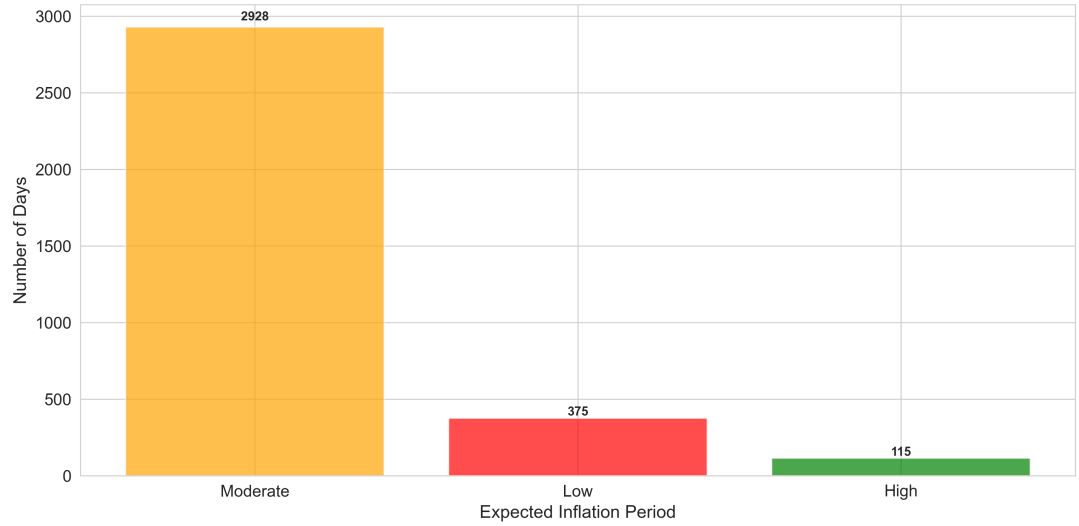
Figures

Figure 1: **10-Year Breakeven Inflation Rate**

Panel A. Breakeven Inflation Rate



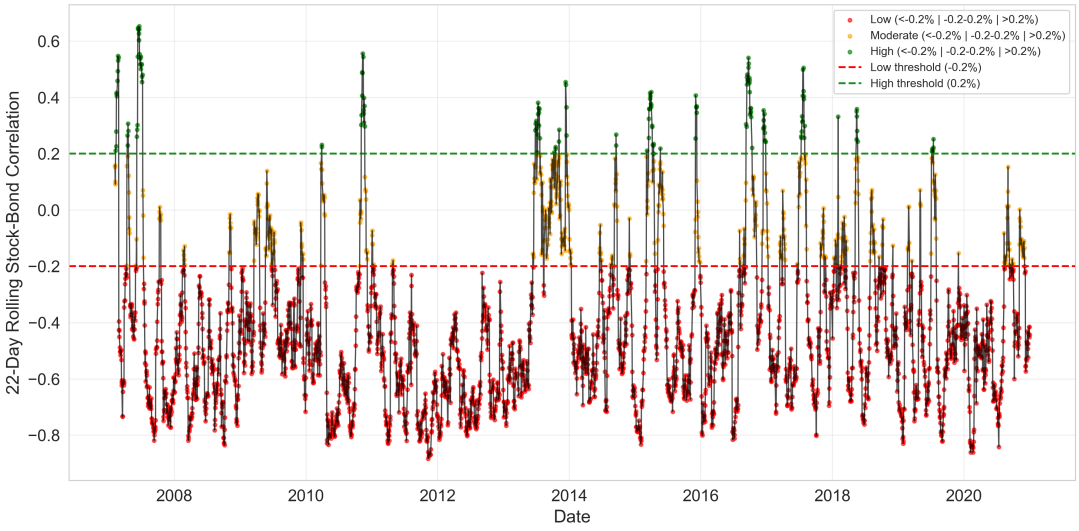
Panel B. Distribution of Inflation Periods



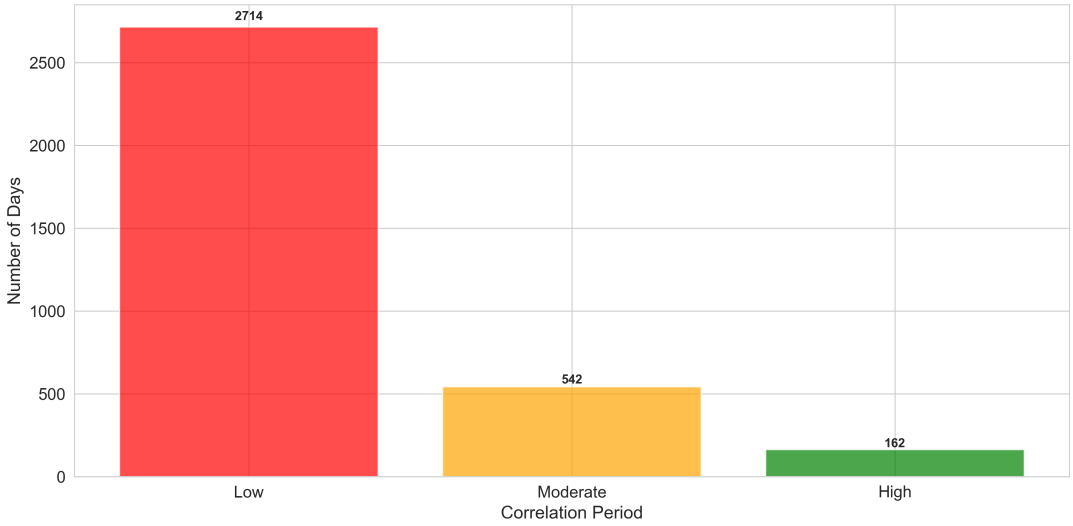
This figure shows the 10-Year Breakeven Inflation Rate from 2007 to 2020 (Panel A) and the distribution of inflation periods, including high, low and moderate inflation periods (Panel B).

Figure 2: **Stock Bond Correlation**

Panel A. 22-Day Rolling Stock Bond Correlation



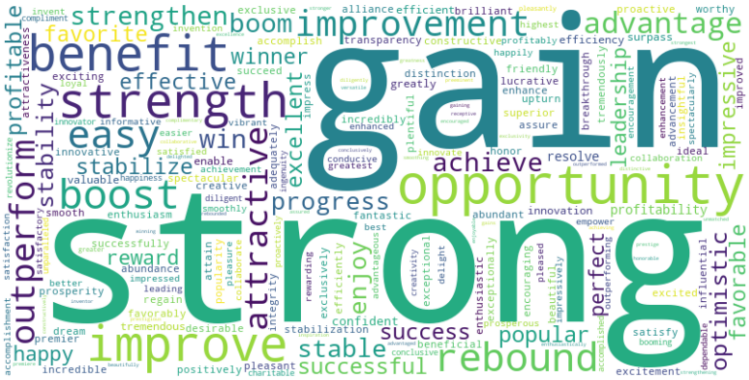
Panel B. Distribution of Correlation Periods



This figure shows the $S\&P500$ and the 10-Year U.S. Treasury Bond returns correlation from 2007 to 2020 (Panel A) and the distribution of correlation periods, including high, low and moderate correlation periods (Panel B).

Figure 3: **Word cloud**

Panel A. Word cloud of positive words

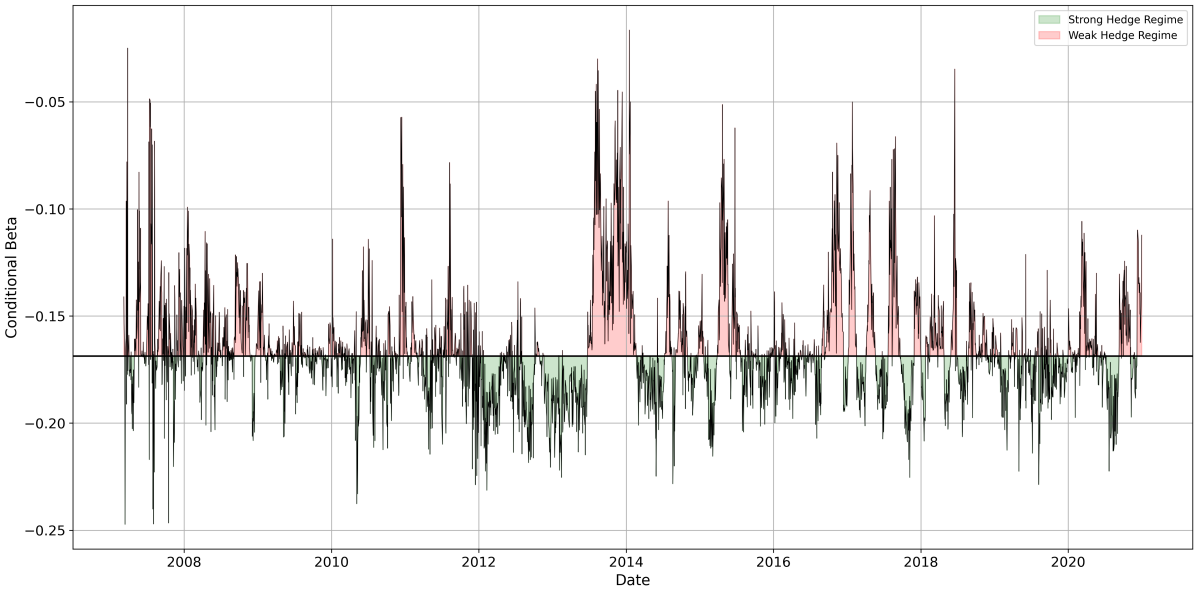


Panel B. Word cloud of negative words



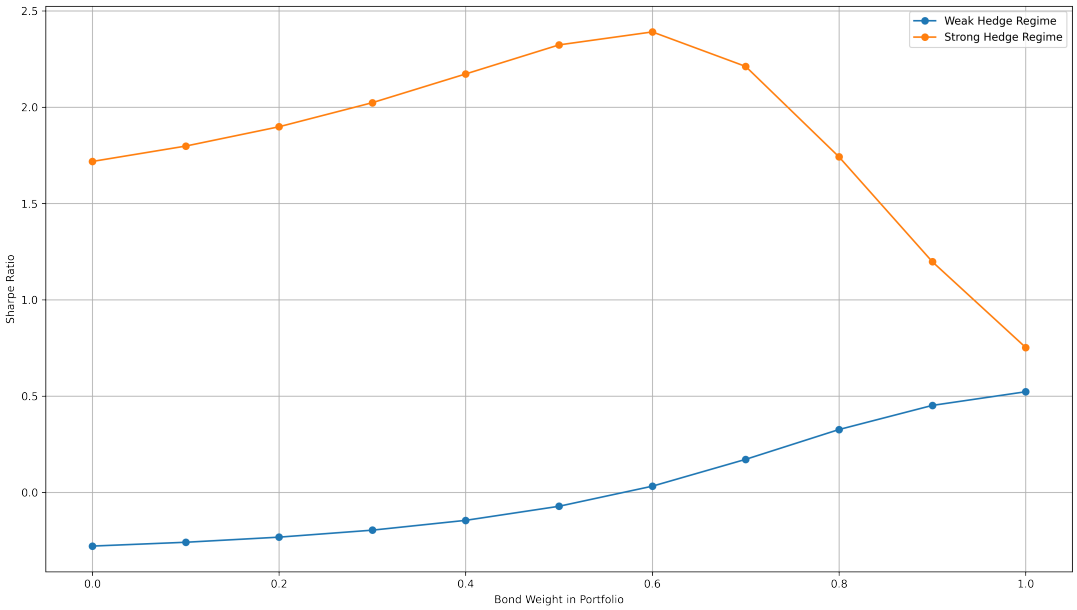
This figure shows the most frequent positive words identified in the Seeking Alpha articles (Panel A) and the most frequent negative words identified in Seeking Alpha articles (Panel B).

Figure 4: **Time-varying Conditional Beta (β_t)**



This figure depicts the calculated conditional beta which represents the sensitivity of bond returns to stock returns for 2007-2020. Green-shaded areas refer to cases for which conditional β_t is less than the median threshold, implying a Strong hedge regime. For cases that conditional β_t is greater or equal to the median threshold, the bond market regime is labelled as Weak hedge regime.

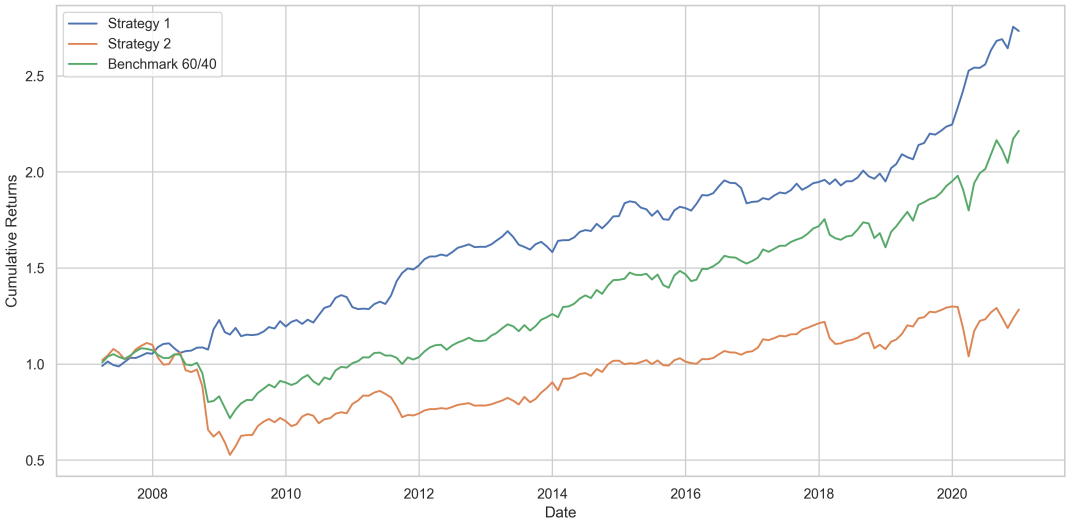
Figure 5: **Annualized Sharpe Ratio**



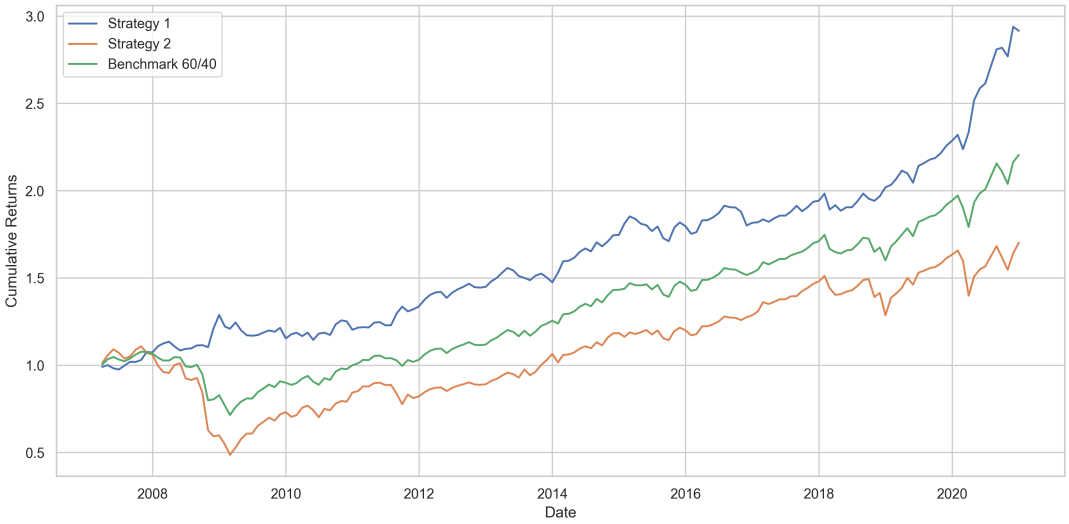
This figure shows the annualized Sharpe ratios of a two-asset portfolio consisting of stocks and bonds, evaluated across different bond weights under the Strong and Weak hedge regime.

Figure 6: **Cumulative Returns**

Panel A. Cumulative Returns per Strategy



Panel B. Cumalative Returns per Strategy (Predicted)



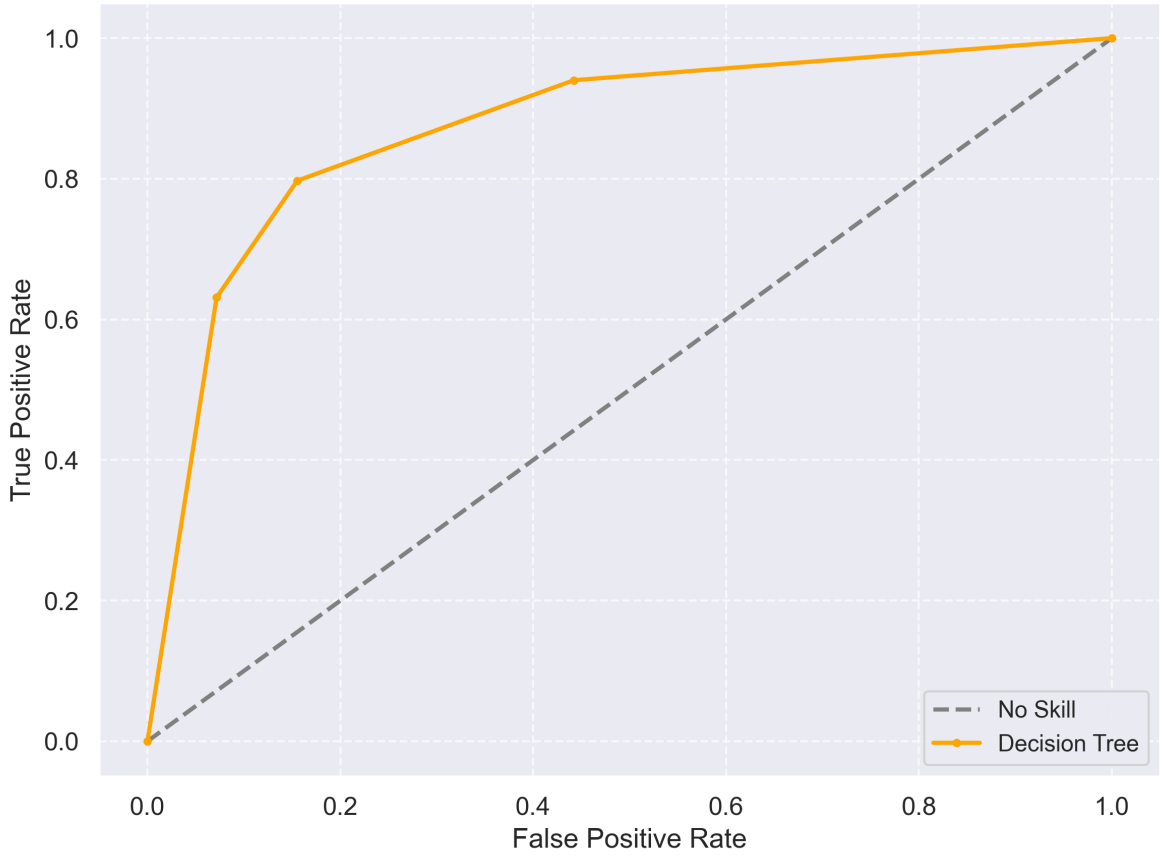
This figure shows the cumulative returns for each strategy. (Panel A) and the cumulative returns per strategy using the predicted bond hedge regimes. (Panel B).

Figure 7: **Rolling R^2 from 252-Day Linear Probability Model**



This figure shows the rolling R^2 values obtained from a 252-day window Linear Probability Model. Higher R^2 values corresponds to periods when the model predicts bond hedge regimes more effectively.

Figure 8: **Receiver Operating Characteristics (ROC) Curve**



This figure shows the receiver operating characteristic (ROC) curve of the Decision Tree Classifier along with the naive classifier.

Tables

5 *S* *B10* *P*

Table 1: **Descriptive statistics**

	S	*B10*	*P*
Panel A: Sample moments			
Mean	0.032	0.018	2.293
Median	0.071	0.008	2.228
Maximum	10.789	4.608	4.928
Minimum	-11.984	-2.707	0.125
Std dev.	1.302	0.493	0.696
Skewness	-0.475	0.238	44.404
Kurtosis	14.600	6.904	327.833
Panel B: Correlation Matrix			
S	1.000		
B10	-0.419	1.000	
P	-0.046	0.049	1.000

This table reports the descriptive statistics and correlation matrix of the market and investor sentiment index for the 2007-2020 period. *S* and *B10* refer to S&P 500 and 10-year Treasury bond daily returns series, respectively. *P* refers to the pessimism sentiment index built using *Seeking Alpha* articles. Panel A reports the descriptive statistics for the 2007-2020 period, while panel B reports the correlation coefficients for the same period.

Table 2: **Investor sentiment and the subsequent 22-Trading-Day stock-bond return correlation**

Investor sentiment

	Summary Statistics of 22-trading day stock-bond return correlations					
Pessimism	Obs	Proportion of $\rho < 0$	Avg.	Median	25%	75%
All	n=3,079	89.40%	-0.475	-0.501	-0.630	-0.339
Pessimism > 0.70	n=758	22.01%	-0.540	-0.563	-0.693	-0.431
Pessimism > 0	n=1,504	43.67%	-0.514	-0.533	-0.667	-0.400
Pessimism > -0.10	n=1,633	47.42%	-0.512	-0.533	-0.668	-0.398
Pessimism > -0.70	n=2,379	69.08%	-0.495	-0.517	-0.650	-0.371
Pessimism < -0.60	n=825	23.95%	-0.411	-0.442	-0.568	-0.241

The table reports on the relation between the investor sentiment level and the subsequent 22-trading-day correlation between stock and 10-year Treasury bond returns. The investor sentiment criterion refers to the investor sentiment level at the end of period $t-1$. The subsequent 22-trading-day correlation refers to the correlation between stock and bond returns over days t through t+21, following the respective P_{t-1}. The correlations are calculated assuming that the expected daily returns for both stocks and bonds are zero, rather than the respective sample means for each 22-trading-day period. Investor sentiment is standardised and negative values mean the difference between negative and positive words is getting narrow, while positive values indicate the negative words are more than the positive words. The 2007-2020 period consists of 3,525 trading days, however some indices do not report for all available dates and after merging the total number of observations is 3,444.

Table 3: **Investor sentiment and the subsequent 22-Trading-Day stock-bond return correlation**

	Stock-bond returns sorted by daily investor sentiment changes					
Investor sentiment Change	Obs	$\mu_{B_{10}}$	$\sigma_{B_{10}}$	μ_S	σ_S	$\rho_{B_{10},S}$
All	n=3,444	0.019	0.493	0.032	1.302	-0.419
0-5th percentile	n=172	0.049	0.445	0.064	1.010	-0.443
0-25th percentile	n=861	0.030	0.463	0.039	1.032	-0.375
25th-50th percentile	n=861	0.014	0.468	0.051	1.116	-0.421
50th-75th percentile	n=861	0.008	0.546	0.023	1.718	-0.412
75th-100th percentile	n=861	0.023	0.493	0.017	1.235	-0.479
95th-100th percentile	n=172	0.066	0.478	-0.040	1.140	-0.590

The table reports on the association between daily investor sentiment changes and the stock-bond return relation. The investor sentiment change criteria refer to the percentile range for the daily change in investor sentiment, from the largest decreases (0 to 5th percentile) to the largest increases (95h to 100 percentile). μ refers to the mean, σ refers to the standard deviation, and ρ refers to the correlation for the stock and bond returns in each respective investor sentiment change grouping. The correlations are calculated assuming that the daily expected returns for both stock and bonds are zero, rather than the subsample mean. The sample period is 2007-2020.

Table 4: **Regression of Bond Returns**

	(1) **Model with Pessimism**	**(2)** **Model without Pessimism**
Constant	0.0002***	0.0002***
	(0.000)	(0.000)
Stock returns (S_t)	-0.1525***	-0.1732***
	(0.020)	(0.020)
Interaction Pessimism × Stock Returns ($Pess_{t-1}S_t$)	-0.0270**	
	(0.014)	
Interaction Correlation × Stock Returns ($\rho^{SB}_{t-22}S_t$)	0.0414	-0.0271
	(0.043)	(0.036)
Interaction Pessimism × Correlation ×× Stock Returns ($Pess_{t-1}\rho^{SB}_{t-22}S_t$)	-0.0710*	
	(0.028)	
Bond Returns (B_{t-1})	0.0053	0.0077
	(0.024)	(0.025)
R^2	0.181	0.177
Adjusted R^2	0.180	0.176
Observations	3399	3399

The regressions are from the Ordinary Least Square model of 1 and 3. The dependent variable is the daily returns on the 10-year U.S. Treasury bond. Model (1) includes the Pessimism Index from the Seeking Alpha articles. Model (2) excludes the Pessimism Index. Standard errors (in parentheses) are heteroscedasticity and autocorrelation consistent (HAC), using the Newey-West estimator with 22 lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: **Annualized Returns and Volatility by Bond Regime**

Metric	**Strong Hedge Regime**	**Weak Hedge Regime**
Stock Return (%)	22.10	-5.22
Stock Volatility (%)	12.86	18.77
Bond Return (%)	5.03	4.07
Bond Volatility (%)	6.68	7.80

This table reports annualized returns and volatilities for stocks and bonds under the strong and weak hedge regime. Returns are calculated from compounded monthly returns derived from daily data. Volatility is the annualized standard deviation of monthly returns.

Table 6: **Performance Summary of Portfolio Strategies: Actual vs. Predicted**

	(1) Actual			**(2) Predicted**		
Metric	Strategy 1	Strategy 2	Static 60/40	Strategy 1	Strategy 2	Static 60/40
Annualized Return (%)	7.77	2.86	6.40	8.38	5.05	6.40
Annualized Volatility (%)	6.55	13.87	9.46	7.94	14.32	9.46
Sharpe Ratio (Annualized)	1.15	0.20	0.66	1.02	0.34	0.66
Max Drawdown (%)	-6.83	-52.49	-33.65	-11.12	-56.08	-33.65

This table reports the annualized performance metrics for three portfolio strategies: Strategy 1, Strategy 2, and a static 60/40 benchmark. Panel 1, presents actual performance, while Panel 2 reports performance under predicted bond hedge regimes. Under both actual and predicted regimes, Strategy 1 allocates 40% to stocks and 60% to bonds in the Strong Hedge Regime, and 0% to stocks and 100% to bonds in the Weak Hedge Regime. Strategy 2 allocates 40% to stocks and 60% to bonds in the Strong Hedge Regime, and 100% to stocks and 0% to bonds in the Weak Hedge Regime. The 60/40 benchmark maintains a constant allocation. Max Drawdown is defined as the maximum observed peak-to-trough decline in cumulative returns over the sample period. All metrics are reported in annualized terms.

Table 7: Classification Performance Summary

Panel A: Confusion Matrix		
Actual \ Predicted	**Weak Regime**	**Strong Regime**
Weak Regime	424 (TN)	78 (FP)
Strong Regime	105 (FN)	413 (TP)
Panel B: Classification Metrics		
Metric		**Value**
Precision		84.11%
Recall		79.72%
F1-Score		81.85%
Accuracy		82.26%

Panel A displays the confusion matrix from the Decision Tree classifier used to predict bond hedge regimes. Rows denote the actual class and columns denote the predicted class. TN = true negatives, FP = false positives, FN = false negatives, TP = true positives. Panel B reports classification metrics computed from Panel A: precision (TP / (TP + FP)), recall (TP / (TP + FN)), and the F1-score, which is the harmonic mean of precision and recall. Accuracy is the percentage of correct predictions overall.

Appendix

A Textual data summary statistics

A breakdown of the *Seeking Alpha* articles and the sections from which they were retrieved can be seen on Table A1

Table A1: **Descriptive Statistics of Raw Seeking Alpha data.**

SA Section	# Articles	%
Market Outlook	82,931	52.5
Commodities	27,501	17.4
Gold & Precious Metals	15,795	10.0
Forex	22,203	14.0
Real Estate	9,607	6.1
Total	**158,037**	**100.0**

This table reports summary statistics for the raw SA articles per theme. The sample period is 2007-2020 and consists of 3,525 trading days.

Table A2 presents the average number of positive, negative and total words per article based on the Loughran and McDonald (2011) lexicon. Panel A reports the summary statistics for all articles. On average there are 436 words, with 18 negative and 8 positive words. It can be assumed that majority of the articles have a negative sentiment. Panel B reports summary statistics for the *Market Outlook* section which mainly contains articles for the stock markets. Then the subsequent Panels refer to the different sections like *Commodities*, *Gold & Precious Metals*, *Forex* and *Real Estate*. For all sections, the content is negatively-focused based on the average number of negative words.

Table A2: **Descriptive statistics of words**

	Mean	Median	25%-quant.	75%-quant.	St. dev.
Panel A: All articles					
Positive words	8	6	3	11	9
Negative words	18	14	7	24	19
Total words	436	353	215	551	363
Panel B: Market Outlook					
Positive words	9	7	3	12	9
Negative words	20	15	7	26	21
Total words	442	353	206	562	394
Panel C: Commodities					
Positive words	8	6	3	10	8
Negative words	15	12	6	20	13
Total words	453	367	233	575	336
Panel D: Gold & Precious Metals					
Positive words	10	7	4	13	9
Negative words	18	14	8	23	16
Total words	524	428	276	653	385
Panel E: Forex					
Positive words	8	6	3	10	6
Negative words	17	15	9	23	13
Total words	372	329	224	460	230
Panel F: Real Estate					
Positive words	6	4	2	8	7
Negative words	16	11	5	22	18
Total words	348	259	142	431	327

This table reports sample statistics of the words per *Seeking Alpha* section. Positive and negative words are mapped using the Loughran and McDonald, 2011 dictionary.

B Sentiment construction

Using the same methodology as in Lachana and Schröder (2025) we first make adjustments for the timing of the *Seeking Alpha* articles. Articles published within the 24-hour window of Monday 16:01 to Tuesday 16:00, are assumed to be referring to Monday trading session. Articles published within the 24-hour window of Tuesday 16:01 to Wednesday 16:00 are assumed to be referring to Tuesday trading session, and so on. (see figure A1)

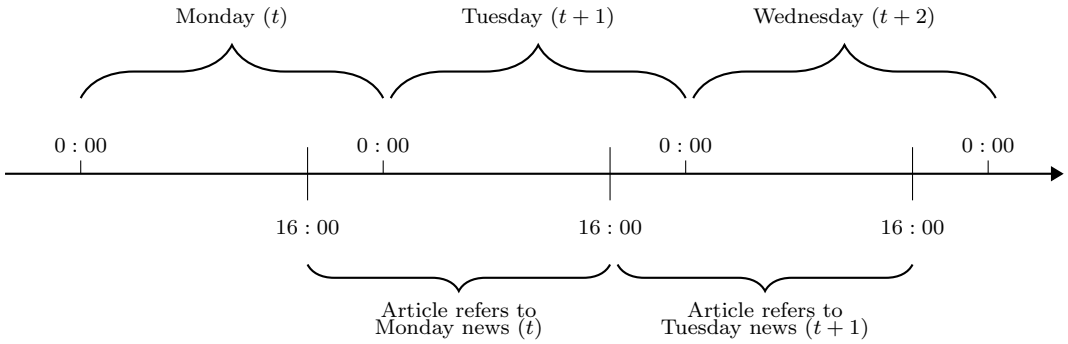


Figure A1: Timeline of an article published on a weekday.

Similarly, the content of articles published between Friday 16:01 ET and Monday 16:00 ET is assumed to be referring to the Friday trading session, and are hence considered "Friday publication". Hence, their sentiment is expected to predict market prices until the market closure of Monday (see figure A2).

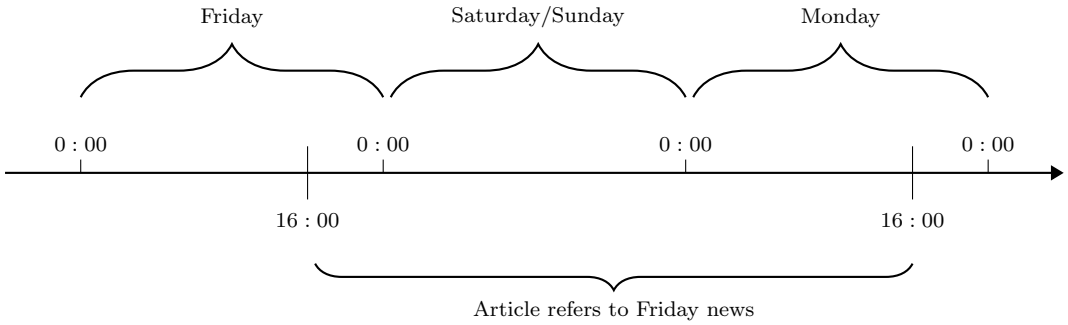


Figure A2: Timeline of an article published on the weekend.

The Loughran and McDonald (2011) contains lists of 2,355 negative and 354 positive words that have been identified as appropriate for assessing the tone or sentiment of finance-related texts. The daily SA sentiment index aggregates all articles appearing in a 24-hour window. Positive and negative sentiment indices are defined as the fraction of positive (negative) words out of total words. For every article and comment i on day t, the number of positive g_{it}, negative b_{it}, and total words, w_{it} is counted. These numbers are then aggregated to construct the daily positive sentiment index $G_t = \sum_i g_{it} / \sum_i w_{it}$, and the daily negative sentiment index $B_t = \sum_i b_{it} / \sum_i w_{it}$. This means that the daily SA sentiment index is a weighted average of the sentiment scores of all SA articles on a given day, where the weight depends on the

number of words in each article (longer SA articles have a greater weight in the daily SA sentiment index). Using the positive and negative sentiment indices, G_t and B_t, this study also calculates a pessimism index as the difference between negative and positive sentiment indices, i.e., $P_t = B_t - G_t$.

Table A3 reports the descriptive statistics for the *Seeking Alpha* sentiment indices. Panel A reports the statistics for all articles and Panel B reports the summary statistics for the *Market Outlook* section. The average value of the pessimism index between the two panels is marginally different.

Table A3: **Descriptive statistics of sentiment indices**

	Mean	Median	25%-quant.	75%-quant.	St. dev.
Panel A: All articles					
Positive	1.932	1.928	1.786	2.068	0.222
Negative	4.221	4.163	3.773	4.601	0.608
Pessimism	2.289	2.224	1.807	2.712	0.692
Panel B: Market Outlook					
Positive	2.030	2.021	1.832	2.211	0.301
Negative	4.503	4.451	4.014	4.958	0.706
Pessimism	2.473	2.433	1.929	3.000	0.831

This table reports sample statistics of sentiment measures obtained from the *Seeking Alpha* articles for the 2007-2020 period. The positive sentiment measure (G_t) is the fraction of positive words out of total words, using the Loughran and McDonald (2011) dictionary. The negative sentiment measure (B_t) is the fraction of negative words out of total words. The pessimism index is the difference between the negative and the positive sentiment measures ($P_t = B_t - G_t$).