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IDENTIFYING PROXY INDICATORS FOR KEY DRIVERS OF ASSET PRICE DYNAMICS

This research examines the challenges of identifying reliable proxy indicators for key drivers of asset price dynamics, with a particular focus on capturing investor expectations regarding the future value of money. While numerous studies have investigated the influence of factors like economic outlook, risk appetite, and inflation expectations, a comprehensive and robust approach to measuring expectations about future interest rate movements remains elusive. This article proposes a novel framework for capturing this crucial factor by developing and testing a proxy indicator based on the regression slope of the yield curve. The study also utilizes the yield spread of Treasury bonds to predict the probability of a recession. The article discusses the rationale behind the chosen indicators and their potential implications for investors and researchers seeking a more accurate understanding of market behavior and informed asset allocation decisions.

Keywords: *economic indicators, recession, asset price dynamics, investor expectations, yield curve, interest rates.*

ВИЗНАЧЕННЯ ПРОКСІ-ІНДИКАТОРІВ КЛЮЧОВИХ ДРАЙВЕРІВ ДИНАМІКИ ЦІН НА АКТИВИ

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У статті розглянуто проблеми ідентифікації надійних проксі-індикаторів ключових факторів, що впливають на динаміку цін на активи, з особливим акцентом на очікування інвесторів щодо майбутньої вартості грошей. Дослідження пропонує новий підхід, який використовує нахил регресії кривої доходності як проксі-індикатор для вимірювання очікувань щодо майбутніх рухів процентних ставок. Цей підхід передбачає проведення регресійного аналізу кривої доходності, що дозволяє визначити зв'язок між процентними ставками та терміном погашення облігацій. Зміна нахилу кривої, отримана в результаті регресії, може бути використана як показник очікувань інвесторів щодо майбутніх змін процентних ставок. Аналіз показує, що нахил кривої доходності має обернений зв'язок з політикою Федеральної резервної системи щодо процентних ставок. Коли інвестори очікують підвищення ставок, нахил кривої падає, переводячи її з нормальної форми в плоску або інвертовану. І навпаки, нахил зростає, коли інвестори очікують зниження ставок. Важливо, що екстремуми нахилу кривої та політики ФРС відбуваються з невеликим часовим запізненням. Це дозволяє припустити, що нахил кривої може бути надійним індикатором майбутніх змін політики щодо процентних ставок. Дослідження виявило, що екстремуми нахилу кривої доходності почали сигналізувати про майбутні зміни в політиці ФРС ще з 1990 року. Однак, слід зазначити, що нахил кривої сам по собі не є надзвичайно точним показником, проте його перехід з нормальної форми в плоску є надійним сигналом про потенційні зміни політики. Цей перехід може бути подальшим об'єктом досліджень для визначення його прогностичної цінності в розробці стратегій розподілу активів. Дослідження також розглядає використання різниці доходності казначейських облігацій для прогнозування ймовірності рецесії. Цей показник є одним з найбільш відомих провідних індикаторів рецесії і може бути корисним для розуміння настроїв інвесторів. Стаття обговорює обґрунтування вибору цих проксі-індикаторів та їхні потенційні наслідки для інвесторів та дослідників, які прагнуть досягти більш точного розуміння ринкової поведінки та обґрунтованих рішень щодо розподілу активів. Це дослідження є основою для майбутніх досліджень, які можуть заглибитись у складні взаємозв'язки між факторами та цінами на активи. Найважливішим майбутнім кроком є оцінка прогностичної сили запропонованих проксі-індикаторів у поясненні дохідності активів. Цього можна досягти за допомогою емпіричного аналізу, використовуючи такі методології, як багатовимірний регресійний аналіз. Крім того, подальші дослідження можуть

вивчити додаткові фактори, що впливають на ціни активів, зокрема акцій, включивши змінні поведінкових фінансів або показники волатильності.

Ключові слова: *економічні індикатори, рецесія, динаміка цін на активи, очікування інвесторів, крива доходності, процентні ставки.*

Statement of the problem. Investors have consistently aimed to maximize their investment portfolio returns. While every investor seeks a favorable return, numerous factors – such as economy growth, interest rates, and inflation – can influence the outcome, impacting various asset classes. Given the significance of investment returns, researchers have developed and employed various models and approaches over the years to help investors estimate potential returns on their investments.

The relationship between macroeconomic variables and financial market profitability has been extensively studied (e.g., [1; 2]). Research shows that factors influencing stock market performance extend beyond financial indicators alone. Specifically, studies highlight that stock prices react to both available information and investor expectations about future performance and profit potential. It is also well-known that financial markets typically incorporate information ahead of time, meaning that asset prices should reflect expectations regarding macroeconomic variables and available data.

Therefore, there is a critical importance of measuring the investors' expectations over the main macroeconomic variables that drives the asset returns. While numerous studies have investigated these drivers, identifying comprehensive and reliable proxy indicators remains a key challenge for researchers and practitioners.

This article aims to contribute into measuring the impact of investors' expectations on asset returns by identifying proxy-indicators which most accurately reflect these expectations. While for some of them these proxy-indicators are well-known and can directly reflect them, like inflation expectations and investors sentiment survey, for the rest like future value of money, we present a novel approach of using the slope of regression on the yield curve as an accurate reflection of these expectations.

Analysis of recent research and publications. Identifying exclusive list of reliable factors impacting the asset prices was always a challenging tasks, which involve extensive studies. While some studies focus on major macroeconomic indicators, e.g., Kaluge D. [3] and Vigliarolo F. [4], others point to the impact of external shocks, such as terrorism, as concluded by Masood O., Javaria K., Petrenko Y. [5], or oil prices fluctuations, as concluded by Masood O., Tvaronavičienė M., Javaria K. [6]. A significant body of research also examines the impact of industry and company performance on stock prices, with studies highlighting the role of factors such as dividend policy, reported by Kumaraswamy S., Ebrahim R.H., Mohammad W.M.W. in their study [7] and company performance (Hilkevics S., Semakina V. [8]). Furthermore, specific studies have investigated the impact of macroeconomic variables on particular industry sectors. For instance, Özlen S. and Ergun U. [9] highlighted the significant influence of exchange rates and interest rates on stock price fluctuations in companies. This demonstrates the diverse range of factors that can influence stock prices, highlighting the need for a comprehensive and nuanced understanding of these drivers to make informed investment decisions.

Setting the task. While the impact of macroeconomic variables like GDP growth, inflation, and interest rates on asset prices has been well-researched, measuring and analyzing investor expectations remains an often-overlooked aspect of market dynamics. Traditional economic data offer valuable insights, but understanding how these data shape investor sentiment and decisions requires a deeper focus on psychological and behavioral factors. This research aims to bridge this gap by identifying and evaluating proxy indicators for key drivers of investor expectations, such as future interest rates, inflation, and economic growth. Since directly measuring investor expectations is challenging, this study will explore alternative indicators to assess their influence on asset returns across various asset classes, providing valuable insights for managing risk and making informed investment decisions.

Summary of the main research material. To our best understanding, the most comprehensive understanding of asset return drivers is provided by A. Shahidi in his work "Balanced Asset Allocation" [10]. Author identifies only three key factors:

1. Changes in expectations regarding the future economic environment (business cycle): unexpected changes in the pace of economic growth and inflation.
2. Changes in risk appetite or overall market willingness to take on risk (changes in risk premium).
3. Changes in expectations about the future value of money (changes in risk-free interest rate).

We interpret Shahidi's perspective to emphasize that all three factors are directly or indirectly linked to investor behavior. Other indicators, including macroeconomic ones that are considered in various studies as influencing factors, merely provide information to investors, based on which a general consensus forms around these three factors. Through this consensus, asset prices are determined via the multitude of decisions made by investors.

As Shahidi notes, if investors anticipate future economic growth, they are willing to pay higher prices for stocks since they expect corporate profits to grow, leading to an increase in stock prices. Conversely, bonds are in lower demand if economic growth deceleration is not anticipated. On the other side, if investors expect an economic downturn, they will demand higher returns from riskier assets like stocks, which will drive stock prices down, while the demand for bonds will increase, pushing their prices up. Thus, not only this factor but others as well affect different asset classes unevenly. For instance, if the market were pricing the 2% economic growth, but the actual growth reaches 4%, stocks will show positive return dynamics. However, if the expected growth was 6% but actual growth is 4%, stock returns might deteriorate significantly despite the economy growing in both scenarios. Similarly, inflation expectations affect returns. Rising inflation increases costs, negatively impacting stock prices as companies may not be able to pass all costs onto consumers, leading to reduced profits. However, this applies to inflation expectations: if high inflation was already priced into assets but actual inflation turns out lower, this would likely trigger price adjustments. Therefore, investor expectations play a crucial role in actual pricing.

General investor apprehension about uncertainty in the global economy typically compels them to seek higher excess returns as compensation for taking on risk. To meet these return expectations, asset prices must decline. For instance, during the latter stages of the 2008 global financial crisis, risk appetite was considerably below average; although markets were recovering, many investors remained reluctant to invest in high-risk assets like stocks at that time.

A leading authority in investment analysis, A. Damodaran, in his recent work, identifies the risk premium as a key determinant in asset allocation within investors' portfolios. "In other words, investors' asset allocation decisions are directly or indirectly influenced by their views on risk premiums and how they differ across asset classes and geographic regions. Thus, if you believe that the equity risk premium is low relative to the risk premium on corporate bonds, you will allocate a larger portion of your overall portfolio to bonds. Your allocation of stocks across geographic markets is determined by your perception of the risk premiums in these markets, with a larger portion of your portfolio directed to markets where the risk premium is higher than it should be (given the risks of those markets). Finally, if you decide that the risk premium in financial assets (stocks and bonds) is too low relative to what you can earn on real estate or other tangible assets, you will shift more of your portfolio into the latter" [11]. Consequently, fluctuations in risk premiums across various assets prompt shifts in portfolio allocations and impact asset dynamics, acting as a catalyst for growth in some assets while contributing to price declines in others. It is evident that the risk premium 'flows' between assets and cannot exert a simultaneous positive (or negative) effect on all assets, including cash. We observed a concurrent shift in the risk premium across most asset classes during the crisis induced by the COVID-19 pandemic in 2020. Notably, nearly all assets, including traditionally defensive ones, experienced significant declines within the first few weeks following the virus's widespread transmission in early March 2020 [12]. The temporary shock triggered such a profound shift in risk appetite that it resulted in extreme scenarios, such as oil futures prices falling below zero. While this was not the sole factor behind the unprecedented price drop, it vividly demonstrates how strongly actual prices are influenced by future expectations. This is further evidenced by the shift in investor risk appetite following the sharp decline in asset prices, leading to renewed buying activity and price increases, even as the worsening pandemic – previously the main driver of sell-offs – continued to unfold.

The direct relationship between this factor and asset pricing is clear: as the cost of money rises, risky assets become less attractive. Typically, the expected future value of money is already reflected in market prices, establishing a consensus on this value. However, when these expectations shift unexpectedly, asset prices are immediately affected. This is often linked to central bank decisions regarding interest rates. For example, in response to a certain event, inflation expectations may increase, prompting investors to adjust their interest rate forecasts – they may expect an earlier or more significant rate hike, or both. As a result, stock prices may decline even if the central bank has neither raised rates nor indicated any future hikes. Subsequently, when investors realize no immediate rate hike is forthcoming, asset prices tend to correct to previous levels. In other cases, the price adjustment may be more prolonged, particularly if rate hikes were unanticipated but ultimately implemented by the central bank.

There is a significant distinction between the actual expectations of the future state of the economy, which are priced into assets, and the general expectations of the households. For example, some survey-based indicators, such as the Consumer Confidence Index, measure the degree of optimism among consumers regarding current and anticipated economic conditions. In certain studies, this index has been documented as a factor influencing stock returns [13]. Similarly, the Business Confidence Index measures businesses' expectations based on assessments by firms of their production, orders, and inventories, as well as their current operational status and short-term assumptions for the future. However, such expectations are not always directly reflected in asset prices. Simply put, an investor may anticipate a worsening economic situation, but this does not necessarily mean they will adjust their portfolio.

Conversely, some indicators can capture actual investor expectations. One widely used in assessing the future economic outlook is the yield curve (of U.S. Treasury bonds). The mechanism by which expectations are incorporated into the yield curve is as follows: the yield curve reflects investor behavior and expectations through their bond market transactions. When investors anticipate substantial future economic growth and higher inflation, they demand higher returns on long-term bonds to compensate for these risks, resulting in an upward-sloping yield curve. As bond yields become less attractive, investors sell bonds, causing bond prices to drop and yields to rise. Conversely, if investors expect an economic slowdown or recession, they prioritize the safety of long-term bonds, driving bond prices up and yields down. For this reason, the difference between long-term and short-term bond yields, known as the yield spread, is used to measure investor expectations about the future economy.

The yield spread is widely used in academic research to estimate the probability of a recession [14]. Originally proposed by [15], this methodology remains in use today. The model incorporates yield spread data alongside recession data (for the U.S. economy), as defined by the NBER. Recession periods are represented as a categorical variable: a value of 1 indicates a recession, while a value of 0 denotes no recession at that time [16]. The methodology involves calculating two functions, the first of which is the log-likelihood function, computed by formula (1):

$$\log L(\beta_0, \beta_1) = \sum_{i=1}^{n} \left[y_i \log P_i + (1 - y_i) \log(1 - P_i) \right] \quad (1)$$

where y_i is the binary recession indicator, and P_i is the predicted probability of a recession for the i_{th} observation, calculated as:

$$P_i = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \cdot \text{spread}_i)}} \quad (2)$$

The optimization algorithm begins with initial assumptions for the coefficients β_0, β_1. The algorithm assigns arbitrary values, which typically start from zero. Using these initial assumptions, the algorithm calculates the predicted probability P_i for each observation using equation (2). Next, the algorithm applies the Maximum Likelihood Estimation (MLE) method, which involves finding the values of β_0, β_1 that maximize the log-likelihood function (1) through iterations, ultimately providing the best estimates for these coefficients. Once the optimization process is complete, the second model – logistic regression – is applied, calculated using equation (3):

$$\log\left(\frac{P(\text{recession})}{1 - P(\text{recession})}\right) = \beta_0 + \beta_1 \cdot \text{spread} \quad (3)$$

where P(recession) represents the probability of a recession, and β_0, β_1 are the coefficients predicted by the optimization algorithm, with 'spread' representing the yield spread.

In prior studies, recession probabilities were typically calculated using monthly data, as the NBER reports recessions on a monthly basis. However, since yield spread data are available at a daily frequency, we opted to convert the NBER recession data into daily format using a linear interpolation method. Specifically, if the recession indicator for a given month is 1 (or 0), the same value is applied to every day within that month, assuming recessions start or end on the first or last day of the month. This approach increases the number of observations and enhances the model's precision.

Data on recessions and the yield spread between 10-year Treasury bonds and 3-month Treasury bills are available from the official website of the Federal Reserve Bank of St. Louis. The spread data are available from 1982, resulting in over 10,000 observations. Since the indicator predicts the probability of a recession occurring within the next 12 months, the actual recession data were shifted backward by 12 months before being applied in the model. Later, when interpreting the results, the data were restored to their actual observation points.

As some studies also use the spread between 10-year and 2-year Treasury bonds for calculating recession probability in addition to the 10-year and 3-month spread, we applied both data sets in this study for comparison purposes. The modeling and calculation results are shown in Figure 1.

Throughout the observation period starting from 1982, the NBER identifies five recessionary periods. Research findings indicate that in all five cases, once the recession probability reached 20% – whether using the spread with 2-year or 3-month bonds – the NBER registered a recession within 12 to 24 months. Compared to the actual onset of recessions, this indicator can be considered a reliable signal of worsening economic conditions anticipated by investors. However, the period beginning in 2022 draws attention. At some point, the recession probability reached a historic 50% for both indicators. Recently, a divergence between the indicators has emerged: the probability of recession based on the 2-year bond spread has been declining, while the probability based on the 3-month spread has been rising.

It remains uncertain whether the sharp increase in recession probability is directly linked to investor concerns following Russia's full-scale invasion of Ukraine. In 2022, most assets exhibited negative returns, including both high-risk assets such as stocks and traditionally safe assets like bonds. Although stock markets began to recover at the start of 2023, eventually surpassing the historical highs reached in 2021, investor apprehensions persist.

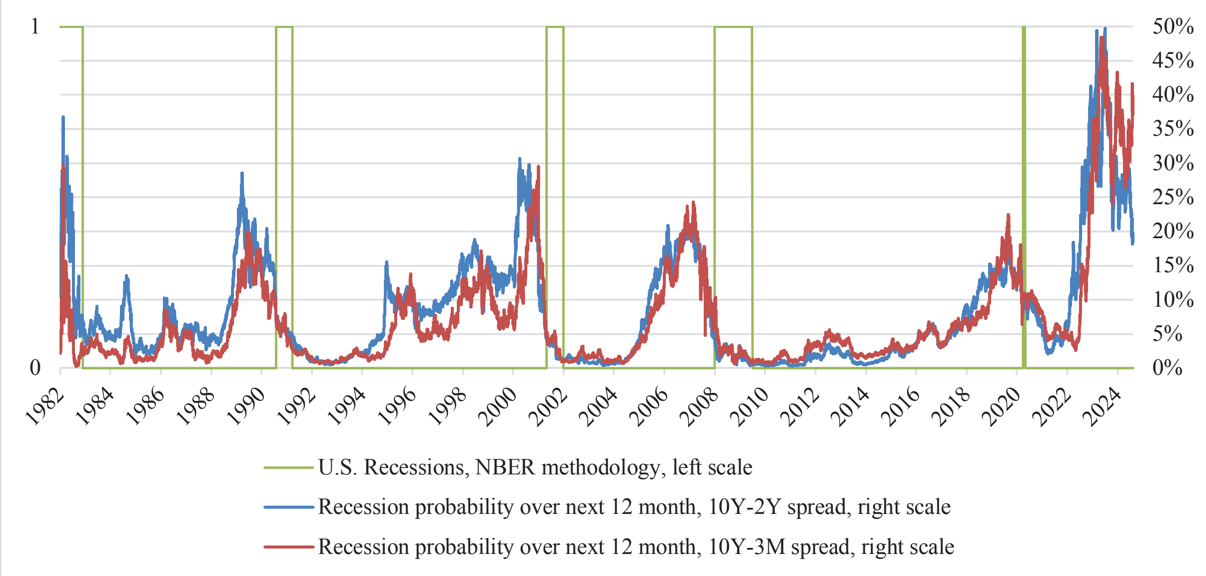

Figure 1. Probability of a recession in the US within the next 12 months. by 10-year and 2-year/3-month bond spreads, 1982–2024

Source: calculated using data from Federal Reserve Bank of St. Louis

This marks the first instance in at least the past 42 years where a) the recession probability reached 50%, and b) despite exceeding the 20% threshold, a recession was not recorded within 12 months, contrary to previous occurrences. Currently, for the indicator based on 2-year bond yields, the period since crossing the 20% threshold has already exceeded 24 months, and for the 3-month bond yields, this period will be surpassed in November 2024.

However, if we introduce an additional condition – such as the probability returning to the 10% level, since historically, recessions have only occurred after this – we will see that this condition has not yet been met. Therefore, it is necessary to wait for this condition to be fulfilled before verifying whether the indicator’s signal was accurate. If the probability falls below 10% and no recession occurs within a year, it is likely that fundamental shifts have altered the interpretation of the indicator, necessitating further investigation. As of now, the recession probability indicator can be considered applicable for assessing investor expectations regarding the future state of the economy.

Regarding the proxy for expectations of future inflation, there are various approaches to measuring this indicator. One of them involves monthly consumer surveys on expected inflation. However, in our case, it is crucial to focus on the expectations of investors specifically. Instead of conducting separate calculations, we can use an existing dataset. For instance, the Federal Reserve Bank of Cleveland estimates the expected inflation rate over the next 30 years, along with the inflation risk premium, real risk premium, and real interest rate. These estimates are derived from a model that incorporates Treasury bond yields, inflation data, inflation swaps, and survey-based measures of inflation expectations. Among this dataset, there is a specific set of data regarding one-year inflation expectations, which can serve as an indicator for measuring inflation expectations. The data are made available by the Federal Reserve Bank of St. Louis.

As mentioned earlier, it is essential not only to assess expected inflation but also to compare it to actual inflation, in order to evaluate the magnitude of the “surprise” for investors. As shown in Figure 2, actual inflation has typically deviated significantly from expected inflation. This discrepancy can directly influence investors' decisions regarding asset allocation in their investment portfolios.

The next indicator is proxy for changes in risk appetite (risk premium). A. Shahidi notes that a measure of this factor can be captured by the “fear and greed” of investors [10, p. 41]. When financial markets exhibit consistent growth, investors tend to accept a lower risk premium, purchasing assets at inflated prices, thus demonstrating “greed”. Conversely, during “bear markets”, investors are often unwilling to buy assets even at prices significantly lower than the average over the past n years, reflecting “fear”.

The American Association of Individual Investors (AAII) conducts a weekly “Investor Sentiment Survey”. This survey serves as a measure of investor “greed and fear”, reflecting individual investors' sentiments regarding the stock market's direction over the next six months. Participants indicate whether they are optimistic (expecting market growth), pessimistic (expecting market decline), or neutral (expecting minimal changes). The survey data is available weekly, enabling its use for analyzing market trends and forecasting future market movements. Figure 3

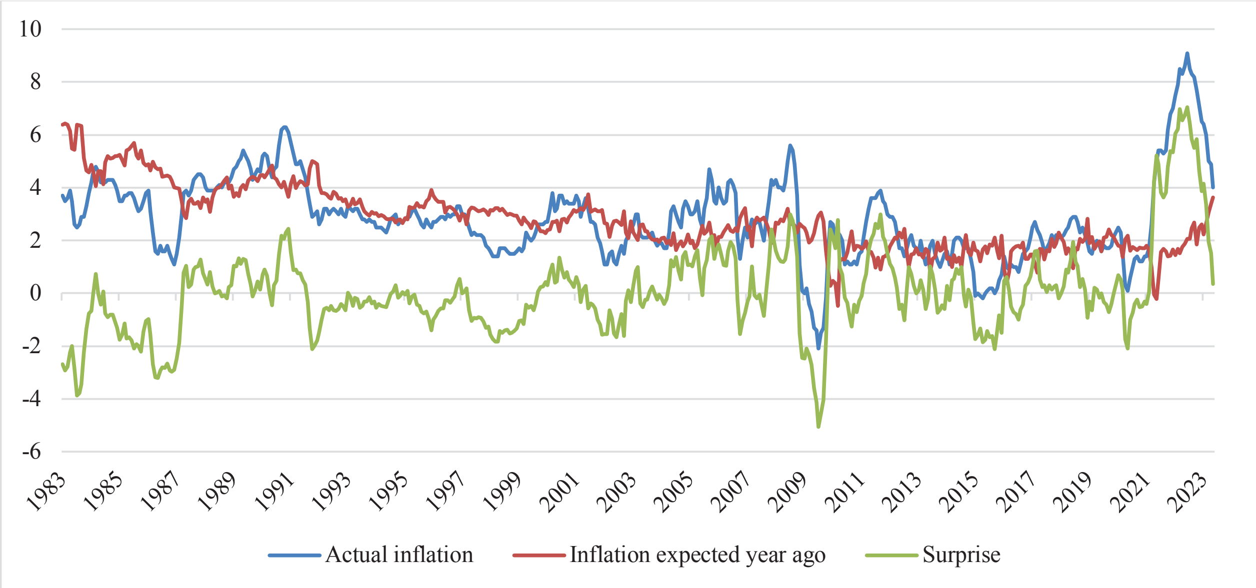

Figure 2. The actual inflation, the expected inflation year ago, and the surprise (difference between actual and expected inflation) of the U.S. dollar, 1983–2023

Source: calculated using data from Federal Reserve Bank of St. Louis

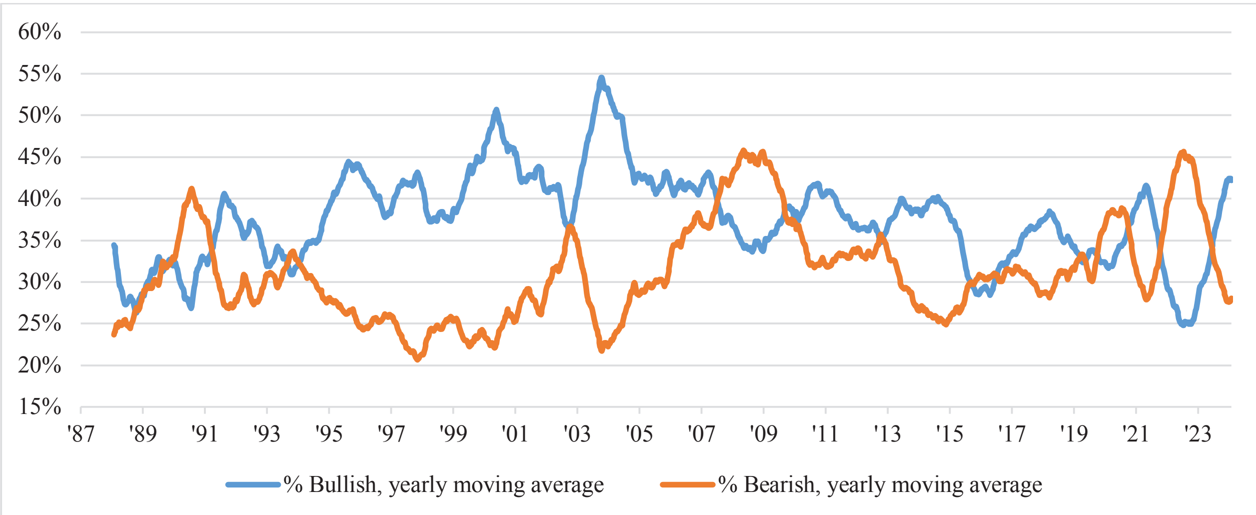

Figure 3. Yearly moving average of bullish and bearish sentiment, 1987–2024

Source: calculated using data from American Association of Individual Investors

illustrates the average sentiment of investors, represented as a 12-month moving average. Clear trends in sentimental changes can be observed at certain intervals.

The last indicator is proxy for expectations of future value of money (risk-free rate of return). Since the cost of money is determined by the yield on risk-free assets, which is influenced by the central bank rate, this factor essentially reflects expectations regarding future interest rate movements. Academic literature provides several proxy indicators for investors' expectations of the central bank rate. [17] identified two indicators that can serve as measures of such expectations: Federal Funds Futures (FFF) and 1- to 12-month Overnight Interest Swaps (OIS) – a swap where the overnight rate is exchanged for a fixed interest rate. However, historical data for these indicators is available only on a commercial basis, with no open-access datasets.

Alternatively, as noted in [18, p. 197], "The yield curve reflects investors' expectations of the future path of interest rates: changes in interest rate uncertainty have a significant impact on economic agents' decision-making, and the yield curve captures these investor expectations". We have already mentioned the yield curve of Treasury bonds in the context of the spread between long-term and short-term bonds to assess the probability of a recession. However, the yield curve itself encompasses not only short- and long-term bonds but the entire spectrum of maturities, and it can take the form of a normal, inverted, or flat curve (see Figure 4).

A normal yield curve suggests that yields increase with longer maturities. This reflects investors' expectations that the economy will grow in the future, which could lead to higher inflationary pressure and force the central bank to raise interest rates to control inflation. In this scenario, long-term bonds become less attractive because investors demand a higher risk premium for longer maturities, accounting for the risk of rising inflation and a decrease in the real yield of such bonds. This, in essence, reflects investors' expectations of an increase in the future cost of money.

An inverted yield curve, on the other hand, indicates that long-term bond yields are lower than short-term ones. Typically, this occurs when there are expectations of a sharp decline in the central bank rate, which usually happens during recessions. A sharp rate cut means that newly issued short-term bonds will have a lower yield than previously issued long-term bonds with a higher rate. This increases demand for long-term bonds, driving up their prices and reducing their real yields. The prospect of a recession also boosts demand for bonds as a safe-haven asset, contributing to the inversion of the yield curve. Therefore, an inverted curve signals investors' expectations of a decrease in the future cost of money.

There is also the possibility of a flat yield curve, where the difference between short-term and long-term yields is minimal. This reflects investor expectations of a gradual decline in the central bank rate, albeit at a slower pace than with an inverted curve. A gradual rate cut suggests an overheating economy, with the Federal Reserve taking timely action to stimulate further growth. This scenario does not indicate an impending recession, but if economic conditions do not improve, the yield curve may eventually invert.

Thus, the yield curve reflects the future cost of money as anticipated by investors. However, the yield curve itself is a "snapshot" representing a specific moment in time. To investigate the impact of this indicator on asset dynamics, the dataset must be presented as a time series. A review of the literature examining the yield curve as an economic predictor reveals that most studies employ either the yield spread between different maturities [19] or various models based on this spread [20].

In fact, all known approaches focus on the difference between specific yields – typically between 10-year and 3-month maturities – similar to the spread we have used as a factor in predicting the likelihood of a recession. While this approach has proven effective for the tasks at hand, it may not fully capture the dynamic nature of the yield curve, which contains information about not just two maturities but up to eight.

To the best of our knowledge, this study introduces a novel approach to using the yield curve as a factor for gauging expectations regarding the future cost of money. This approach involves applying regression analysis to each observation point to measure the slope of the curve, which serves as the basis for the indicator. This method offers several advantages over using a yield spread:

1. The regression slope considers the entire yield curve, rather than just two points. This holistic approach can uncover underlying patterns and relationships across different maturities, providing a more comprehensive view of market expectations regarding future interest rates and economic activity.

2. The regression slope is sensitive to changes across all maturities, making it a more precise indicator. This sensitivity can help detect early signs

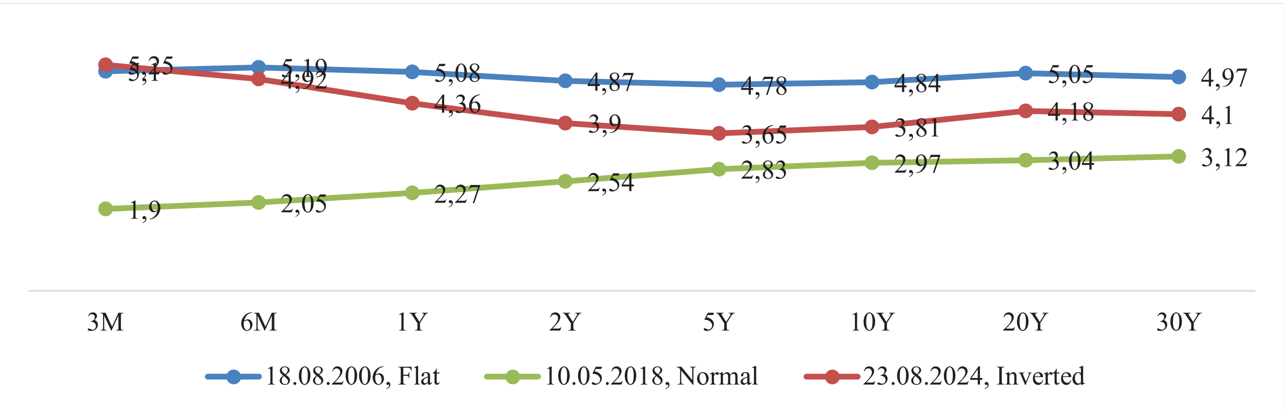

Figure 4. Yields of normal (as of May 10, 2018), inverted (as of August 23, 2024), and flat (as of August 18, 2006) US government bond yield curves

Source: calculated using data from Federal Reserve Bank of St. Louis

of economic shifts, enabling more timely and accurate forecasts.

3. The yield spread between two maturities can be influenced by short-term market fluctuations and other anomalies. The regression slope, by averaging these fluctuations across multiple maturities, can provide a smoother and more reliable signal of market expectations.

The regression formula for the yield curve can be expressed as follows:

$$Y_t = \beta_0 + \beta_1 X_t + \epsilon_t \tag{4}$$

where Y_t is the yield at time t, X_t is the maturity at time t, β_0 is the constant (intercept), β_1 is the slope of the regression line, and ϵ_t is the error term.

In this regression model, the slope coefficient β_1 represents the degree of change in yield relative to the maturity period. By calculating β_1 on a daily basis, we can observe how the relationship between yield and maturity evolves over time, providing a dynamic and comprehensive indicator of market expectations and economic sentiment.

In Figure 5, the maturities are depicted from 1 to 8, corresponding to 3-month, 6-month, 1-year, 2-year, 5-year, 10-year, 20-year, and 30-year U.S. Treasury bonds, respectively. The regression trend line, calculated using the least squares method, is marked with dashed points. The regression formula is displayed directly on the graph, allowing for a visual comparison of the slope coefficient and the trend line. As seen, the stronger the trend, the larger the slope coefficient. This relationship holds true for an inverted yield curve as well, where a smaller slope coefficient indicates a steeper inversion. Conversely, the closer the slope coefficient is to zero, the flatter the yield curve, which is particularly evident for the curve observed on May 22, 2007.

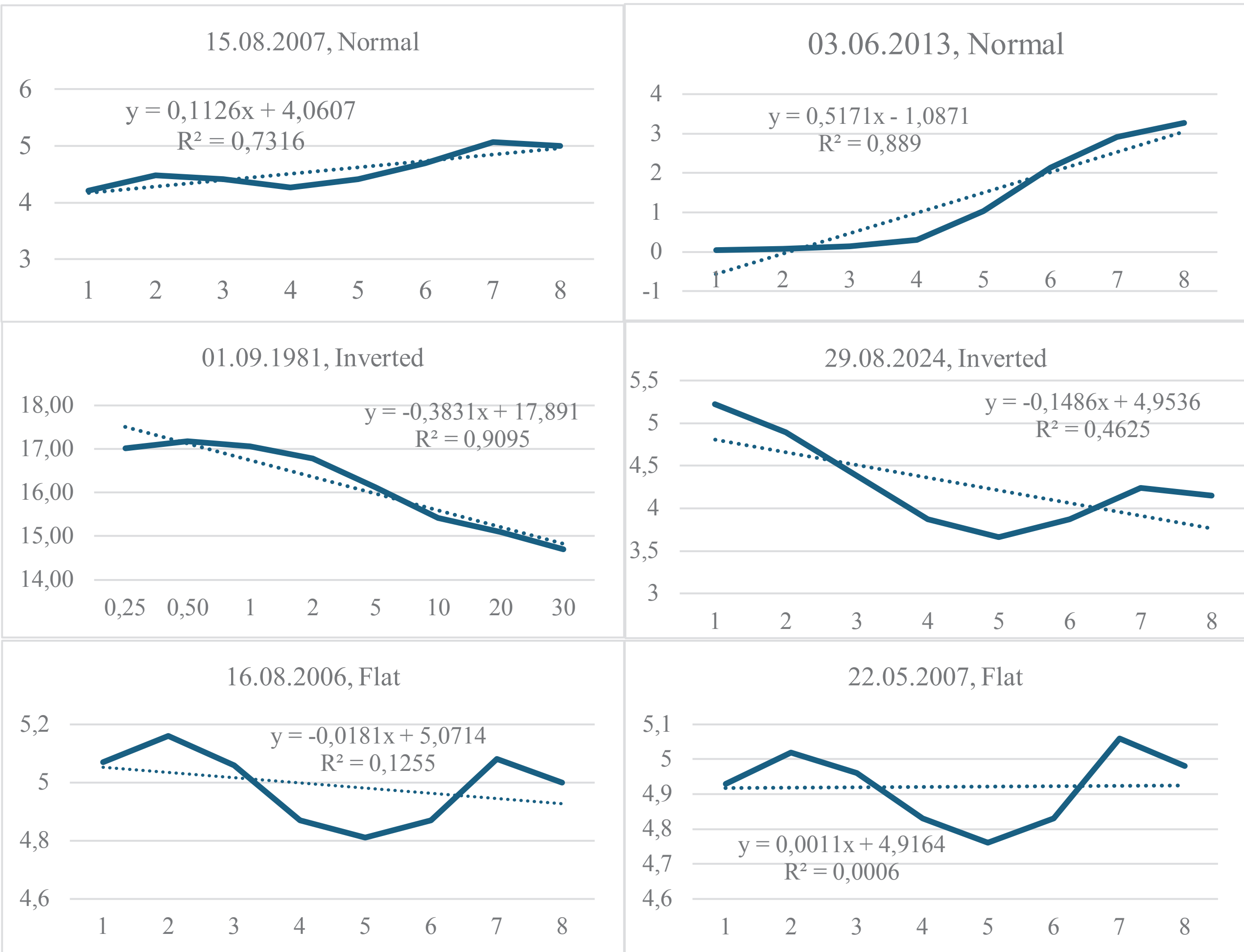

Figure 5. Demonstration results of regression analysis on some observation points covering all three types of yield curve

Source: calculated using data from Federal Reserve Bank of St. Louis

Based on our estimates, a slope coefficient within the range of <0,02 and >-0,02 signals a flat yield curve, >0,02 indicates a normal curve, and <-0,02 suggests an inverted curve.

Thus, the magnitude of the slope coefficient of the yield curve reflects not only the "category" of investor expectations, such as in the traditional division of the curve into normal, flat, or inverted, but also the "strength" of these expectations, allowing us to identify extremes in these expectations. In Figure 6, the slope coefficient is depicted with the categorization of the yield curve, alongside the Federal Reserve's policy rate (i.e., the cost of money), both actual and shifted by one year. This allows for a visual comparison of extremes with a time lag and provides an opportunity to evaluate the predictive power of the indicator.

The graph provides several important insights. First, the slope coefficient of the yield curve exhibits an inverse relationship with the Federal Reserve's policy rate. When investors anticipate a rate increase, the slope coefficient declines, causing the curve to shift from a normal to a flat or inverted shape. Conversely, the slope coefficient rises when investors expect a rate cut. Second, the extremes of both the slope coefficient and the policy rate occur with only a slight time lag between them. This is a critical observation: if this time lag remains consistent over the entire observation period, it may indicate that the slope coefficient is a reliable predictor of future changes in the policy rate.

To assess the predictive ability of the slope coefficient, we identified the extremes in both data series, as illustrated in Figure 7. The extremes in the policy rate were defined as the points when the rate either began to increase or decrease. To detect the extremes in the slope coefficient, we used the `find_peaks` function from the `scipy.signal` package in Python (Spyder IDE), with the key parameter `prominence = 0.07` to ensure significant peaks were captured.

The results of the comparison of extremes are presented in Table 1. Yield curve slope extremes began signaling future changes in the Federal Reserve's interest rate trajectory as early as 1990. During the period from 2010 to 2015, the slope of the curve signaled two potential rate changes, whereas in 2019, the extreme occurred after the rate adjustment had already taken place. Analyzing all 14 observations reveals an average lead time of 226 days between the curve's extreme and a rate change, with a standard deviation of 619 days. However, when considering only the differences highlighted in green in the table, the average lead time increases to 264 days, with a reduced standard deviation of 207 days.

Therefore, while yield curve extremes alone do not provide highly precise signals of forthcoming rate changes, the transition of the curve from a normal to a flat state itself serves as a reliable warning signal. This transition could be further tested for its predictive value in the development of asset allocation strategies.

Conclusions from the study. This article has presented a framework for identifying proxy indicators for four key drivers of asset price dynamics: changes in economic outlook, risk appetite, inflation expectations, and expectations regarding the future value of money, where for last one the novel framework was presented.

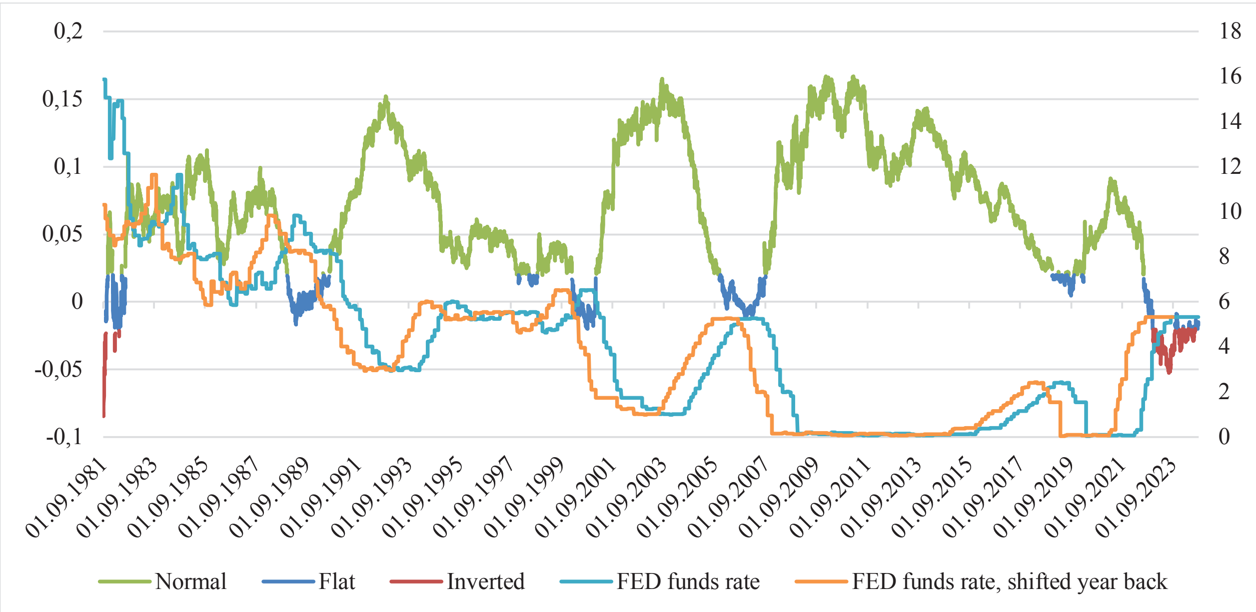

Figure 6. The slope of the regression curve, left scale, split into three states, and the Fed funds rate, right scale, actual and lagged one year

Source: calculated using data from Federal Reserve Bank of St. Louis

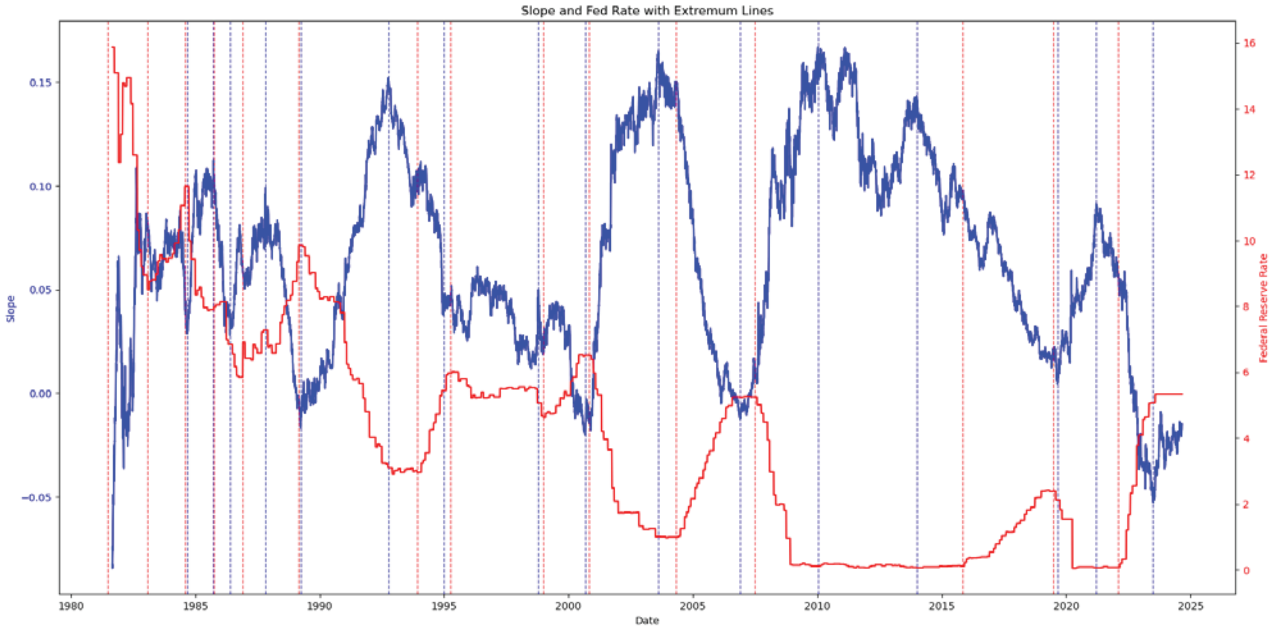

Figure 7. The slope of the regression curve, left scale, and the Fed funds rate, right scale, with extremums

Source: calculated using data from Federal Reserve Bank of St. Louis

Table 1

Results of calculating the time interval between the curve signal (extremum of the curve) and the extremum of the FED funds rate

Slope extremums	FED funds extremums	Difference, days	Descriptive statistics of difference in days	
25.09.1985	01.08.1984	-420	Mean	226
26.05.1986	01.10.1985	-237	Standard Error	165,5648
29.10.1987	01.12.1986	-332	Median	83
28.03.1989	01.03.1989	-27	Mode	–
06.10.1992	01.12.1993	421	Standard Deviation	619,4869
01.01.1995	01.04.1995	90	Sample Variance	383764
17.10.1998	01.01.1999	76	Kurtosis	7,159057
04.09.2000	01.11.2000	58	Skewness	2,377431
13.08.2003	01.05.2004	262	Range	2540
23.11.2006	01.07.2007	220	Minimum	-420
11.01.2010	01.11.2015	2120	Maximum	2120
31.12.2013	01.11.2015	670	Sum	3164
27.08.2019	01.07.2019	-57	Count	14
18.03.2021	01.02.2022	320		
01.07.2023	?	?		

Source: calculated using data from Federal Reserve Bank of St. Louis

The chosen proxy indicators demonstrate a strong ability to capture actual market expectations and provide valuable insights into the interplay of these factors across different asset classes and investment horizons. The findings suggest that utilizing these indicators can enhance investors' ability to make more informed decisions about portfolio allocation and navigate periods of market volatility.

This study presents a foundation for future research that can delve deeper into the complex relationships between these factors and asset prices. First, the most important future step is to assess the predictive power of these proposed proxy indicators in explaining asset returns. This can be achieved through empirical analysis, employing methodologies such as multivariate regression analysis. By examining the relationship between the identified proxy indicators and asset returns across various asset classes and investment horizons, researchers can quantify the extent to which these factors influence market behavior. Such an analysis would not only validate the relevance of the proposed indicators but also provide valuable insights for investors seeking to optimize portfolio allocation strategies based on these key drivers of market dynamics. In addition, further research can explore additional factors influencing asset prices, particularly for equities, incorporating behavioral finance variables or volatility measures to improve model accuracy. Exploring non-linear relationships and incorporating machine learning techniques might allow for a more nuanced understanding of how different factors interact with asset prices over time, especially during periods of heightened uncertainty. Employing dynamic models, such as time-varying coefficient models or regime-switching approaches, could offer insights into how these factor relationships change in response to economic cycles or geopolitical events. Research can also examine how factor dynamics differ across various regions, providing a more comprehensive view of the global investment landscape. Finally, developing more robust models that incorporate forward-looking data, real-time economic indicators, and enhanced expectations measures could further improve the ability to predict asset price dynamics, ultimately providing investors with better tools for long-term portfolio management. By contributing to formulating a practical framework for capturing investor expectations, this study opens a pathway for further research and improved investment decision-making.

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