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REGRESSION ANALYSIS OF THE IMPACT OF KEY DRIVERS OF ASSET PRICE DYNAMICS

РЕГРЕСІЙНИЙ АНАЛІЗ ВПЛИВУ КЛЮЧОВИХ ДРАЙВЕРІВ ДИНАМІКИ ЦІН НА АКТИВИ

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The research is devoted to provide understanding on how different macroeconomic and behavioral factors impact asset prices dynamics and potentially possess predictive power for future returns. Utilizing a multi-factor regression analysis, the study investigates the influence of recession probability, inflation surprises, investor sentiment, and yield curve slope on the returns of 35 diverse asset classes across varying investment horizons (3 months, 6 months, 1 year, 2 years, and 5 years). The findings reveal that the chosen proxy indicators effectively capture the influence of these factors, with predictability of asset returns generally increasing with longer investment horizons. Furthermore, the analysis demonstrates that different asset classes exhibit varying sensitivities to the identified factors. This research provides valuable insights for investors seeking to manage risk and make informed asset allocation decisions, leading to more efficient portfolio management.

Keywords: asset price dynamics, investor expectations, multi-factor regression analysis, asset allocation, investment management, financial markets.

Це дослідження присвячено аналізу впливу ключових макроекономічних показників на динаміку цін активів різних класів та інвестиційних горизонтів. Актуальність теми зумовлена постійною потребою інвесторів у вдосконаленні методів прогнозування та управління ризиками. Розуміння того, як макроекономічні фактори впливають на поведінку інвесторів та ціни активів є критично важливим для розробки ефективних інвестиційних стратегій. В рамках дослідження проведено регресійний аналіз взаємозв'язку між динамікою цін 35 різних класів активів, включаючи акції, облігації, сировинні товари та альтернативні інвестиції, та такими макроекономічними показниками, як ймовірність рецесії, непередбачувані зміни інфляції, настрої інвесторів та нахил кривої дохідності. Для кожного класу активів та інвестиційного горизонту (3 місяці, 6 місяців, 1 рік, 2 роки та 5 років) було побудовано окрему регресійну модель, для оцінки впливу макроекономічних факторів на дохідність цих активів. Результати дослідження свідчать про неоднорідний вплив вибраних макроекономічних факторів на різні класи активів. Виявлено, що облігації та сировинні товари демонструють більш високу чутливість до змін макроекономічних показників, ніж акції. Це можна пояснити більшою залежністю цін на ці активи від об'єктивних економічних факторів, тоді як динаміка цін на акції значною мірою визначається суб'єктивними очікуваннями та поведінкою інвесторів. Також встановлено, що прогнозованість дохідності активів зростає зі збільшенням інвестиційного горизонту. Це підтверджує доцільність довгострокового інвестування та дає підстави для розробки більш ефективних стратегій розподілу активів на довгострокову перспективу. Практична цінність дослідження полягає в тому, що отримані результати можуть бути використані інвесторами для оптимізації своїх портфелів з урахуванням прогнозованого впливу макроекономічних факторів. Зокрема, розуміння залежності дохідності активів від ймовірності рецесії, інфляції, настроїв інвесторів та нахилу кривої дохідності дозволяє більш ефективно управляти ризиками та підвищувати прибутковість інвестицій. Дослідження також дає підстави для подальших наукових розвідок в галузі фінансової економетрики та розробки більш складних моделей прогнозування динаміки цін активів.

Ключові слова: динаміка цін на активи, очікування інвесторів, багатофакторний регресійний аналіз, алокація активів, інвестиційний менеджмент, фінансові ринки.

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Statement of the problem. This research is a continuation of our previous study [1], where we identified the factors which are being considered as main impact factors on asset price, such as changes in economic outlook, risk appetite, inflation expectations, and expectations regarding the future value of money. Furthermore, to represent these factors as data series, available for further analysis, the following proxy indicators were identified, such as U.S. recession probability based on Treasuries' yield spread, inflation surprise based on the Federal Reserve Bank of Cleveland inflation expectations estimates, bullish-bearish investors' sentiment based on the American Association of Individual Investors' "Investor Sentiment Survey", and also a novel approach were developed based on the regression slope of the yield curve to represent expectations regarding the future value of money.

If we could say that asset prices are essentially driven by investor behavior, it would be reasonable to put a hypothesis that, in practice, the influence of various factors on asset price dynamics is mediated through investor behavior: "Asset prices reflect investors' beliefs about the future. Our understanding of how these beliefs are formed, how they evolve over time, and how we can measure them is still limited" [2]. From this, we can infer that asset price movements may be explained if we can identify macroeconomic indicators that effectively extrapolate investor behavior, allowing these indicators to be used for analyzing their impact.

While previous studies have explored macroeconomic factors influencing asset prices, a more comprehensive understanding is needed to fully capture the interplay of factors with investor's expectations and real economic conditions. The selected four proxy indicators developed to effectively capture both, potentially exploring the possibility of having a predictive power, as market prices usually tend to foresee future risks and effectively determine their probabilities, which being said, is due to investors' expectations and their respective response to these expectations. Therefore, the next step is to investigate the impact of these factors, using proxy indicators, on the asset price dynamics.

Analysis of recent research and publications. Many studies have focused on identifying the factors that influence asset price movements. Some works also provide a comprehensive analysis and synthesis of the broader literature on this subject. One such study by Verma R. K. and Bansal R. found that macroeconomic indicators are the most frequently analyzed factors [3]. Among asset classes, equities have received the most attention. For example, Bhuiyan E. M. and Chowdhury M. demonstrated the existence of a long-term equilibrium relationship between the macroeconomic factors such as money supply, real economic activity, long-term interest rates, and the S&P 500 index [4]. The study of Cenedese G. and Mallucci E. analyzed both stock and bond market and have findings regarding financial news, such as news of dividends growth and inflation news driving the returns of stocks and bonds, respectively [5]. The CAPM model, developed in 1960s, and recently updated by Fama and French [6], is widely used to estimate the cost of capital and corporate returns required to invest in corporate assets, as being explained by Rossi M. [7] and as noted by Mandala J. [8], is attractive because it provides powerful and intuitive projections of expected returns and risks and overall risk management. However, it is also reported that the experimental results of this model are still below average as per findings of Acheampong P. and Swanzy S. K. [9].

Moreover, the review of existing literature reveals a limited number of studies that examine a broad range of asset classes and investigate whether there are universal factors influencing asset prices. This is understandable, as identifying a comprehensive set of factors that affect all types of assets is a non-trivial task for individual researchers. Extensive analysis requires substantial human and computational resources, which is why the modeling of such factors is typically undertaken by large multinational asset management corporations. For instance, Barua T. and Barua S. in their study [10] noted that BlackRock reported a 35% increase in portfolio returns due to machine learning and predictive analytics. In this respect, it is important and beneficial for individual investors to shed light on factors which they might use for their allocation models as well, leading to an increase in portfolio returns.

Highlighting previously unresolved parts of the overall problem. This research aims to address the gap in understanding whether selected factors, which broadly represents the investors expectation regarding economic conditions: 1) have enough predictability power, and therefore, potentially can be used in asset allocation models to adjust portfolio's asset allocation, leading to efficient avoiding of portfolio losses due to changes in investors' expectations and/or economic conditions and

2) whether these factors uniformly impact the prices of different asset classes.

Setting the task. To address the abovementioned gaps, we intend to apply multi-factor regression analysis not only for the broad range of selected asset classes, but also for different investment horizons to check whether impact differs based on holding period.

Summary of the main research material. Building upon the data collection and methodology outlined in our previous research [11] and [1], this study utilizes a comprehensive dataset of 35 asset classes, encompassing a broad spectrum of investment categories. The selection of asset classes is informed by our previous analysis of asset allocation strategies, responses to geopolitical events, and the common approach found in relevant literature. While different studies have utilized varying numbers of asset classes, our choice of 35 asset classes reflects a balance between comprehensiveness and manageability, aiming to capture a broad range of investment opportunities while maintaining analytical feasibility.

The raw data was obtained from various sources, including Yahoo Finance, Federal Reserve Economic Data (FRED), Kaggle, and Stock Analysis, with ETF data serving as the primary source whenever available. This ensures that the analysis reflects actual returns achievable through ETF investment, providing practical insights for investors. In cases where ETF data was not readily available or the historical period was limited, the corresponding index or commodity price data was used, with tracking error analysis [12] employed to confirm data alignment.

Table 1 presents the selected asset classes and their corresponding ETFs or indices, highlighting the specific data used for each asset class. The dataset encompasses daily data, except for the price of copper, which was converted to daily data using linear approximation.

The rolling returns for each asset class were calculated for periods of 3 months, 6 months, 1 year, 2 years, and 5 years, using the same methodology described in our previous study. This methodology incorporates both simple returns from price changes and returns from dividends.

The summary statistics of rolling returns for the selected asset classes highlight a wide range of performance characteristics. While some assets, like U.S. broad-based short-term investment grade bonds (BSV) and U.S. long-term bonds (TLT), exhibit relatively low volatility, others demonstrate significantly higher volatility, such as oil (DBO) and Bitcoin (GBTC). The average yearly returns for the majority of the asset classes fall within a narrow range, suggesting that long-term investment strategies require a diversified portfolio to mitigate risk. Notably, the mean yearly return for uranium (URA) is negative, indicating that, on average, the investment in uranium has resulted in losses over the period analyzed. These findings underscore the importance of considering individual asset performance characteristics and carefully diversifying investments to manage overall portfolio risk. For a more detailed exploration of the specific returns for each asset class, please refer to our previous work [11].

To determine the impact of various factors on asset price dynamics, we will apply a multifactor linear regression model. Let us define the variables as follows:

– prob: the calculated probability of a recession within the next 12 months based on the yield spread of Treasury bonds,

– surprise: the difference between actual inflation and the inflation expected 12 months prior,

– Bullish: the percentage of investors, according to AAII survey data, who expect the market to rise over the next 6 months,

– Bearish: the percentage of investors, according to AAII survey data, who expect the market to decline over the next 6 months,

– Slope: the slope coefficient of the regression model for the yield curve.

In this case, the regression model is defined by the following formula (1):

$$R_t = \text{const} + \beta_1 * \text{prob}_t + \beta_2 * \text{surprise}_t + \\ + \beta_3 * \text{Bullish}_t + \beta_4 * \text{Bearish}_t + \beta_5 * \text{Slope}_t \quad (1)$$

Where:

– R_t represents the dependent variable (asset price or return),

– const is the intercept,

– β_1, β_2, β_3, β_4, β_5 are the coefficients for the respective independent variables,

This model allows us to estimate the effects of each factor - recession probability, inflation surprises, investor sentiment, and the yield curve slope - on the dependent variable, providing a framework for understanding how these factors influence asset prices.

The descriptive statistics of the factors are presented in Table 2. It is important to note

Table 1

Selected asset classes and representative ticker(s) or index

Broad asset classes	Selected asset class	Representative ticker(s) or index
U.S. equities	U.S. broad equity	Wilshire 5000 Total Market Index
	U.S. Large cap (S&P 500 index)	SPY
	U.S. sectoral equities	XLE, XLU, XLK, XLB, XLP, XLY, XLI, S&P Communication Services Select Sector Index, XLV, XLF, IYR
	U.S. growth equities	IUSG
	U.S. value equities	IUSV
International equities	Developed countries' equities ex.-U.S.	VEA
	EU equities	EZU
	Japan equities	EWJ
	Developing countries' equities ex.-China	EMXC
Precious metals	Gold	LBMA Gold Price PM ($/ozt)
	Silver	LBMA Silver Price ($/ozt)
	Platinum	Platinum London PM Fix ($/ozt)
	Copper	FRED Global price of Copper ($/ton)
Oil, Energy, and Agriculture commodities – exposure	Oil	DBO
	Uranium	URA
	Agriculture commodities	DBA
Alternative investment – exposure	Cryptocurrency – Bitcoin	GBTC
Government bonds – exposure	U.S. Long-term bonds	TLT
	U.S. Mid-term bonds	IEF
	U.S. Inflation-linked bonds	TIP
	Developing countries' government bonds	EMB
Corporate bonds - exposure	U.S. Corporate bonds	VCIT
	International corporate bonds	CEMB
Mixed bonds – exposure	T-Bills, Corporate, MBS and Agency Bonds	BND
	Broad-based short-term investment grade	BSV

Source: [11]

that all factors have been adjusted to daily granularity. The data for the factors probability and slope are already calculated on a daily basis, whereas *Bullish* and *Bearish* are collected weekly, *surprise* is collected monthly. For these three factors, the forward fill method was applied, assuming that investors are aware of the latest available information throughout the entire period until it is updated. This method is used to fill in missing values by carrying forward the most recent observed value.

This technique ensures consistency in the time series data and maintains a uniform daily frequency, allowing for the regression analysis to be performed without gaps. It also reflects the realistic assumption that investors form expectations based on the most recent information available until new data is provided.

An essential part of preparing data for multiple linear regression is testing the factors for multicollinearity. Multicollinearity occurs when there is a linear dependency between two

Table 2

Descriptive statistics of selected factors

	probability	surprise	Bullish	Bearish	Slope
count	11125	11125	9676	9676	11125
mean	0,070	-0,290	0,377	0,310	0,067
std	0,078	1,596	0,101	0,097	0,050
min	0,002	-7,200	0,120	0,060	-0,053
25%	0,020	-1,300	0,302	0,240	0,030
50%	0,043	-0,300	0,373	0,297	0,066
75%	0,094	0,600	0,440	0,370	0,105
max	0,484	5,400	0,750	0,703	0,167

Source: calculated by authors

or more independent variables in a regression model. This issue can lead to several problems, including:

– Bias in parameter estimates: the regression coefficients may become inaccurate, making the interpretation of results more challenging.

– Increased variance of estimates: this can lead to high variability in the parameter estimates, reducing their reliability.

– Insignificant parameters: even if the model has a high coefficient of determination (R^2), individual coefficients may be statistically insignificant.

In scientific literature, the Variance Inflation Factor (VIF) is widely used to assess the degree of multicollinearity between independent variables in a regression model. VIF for each independent variable is calculated using the formula (2):

$$\mathrm{VIF}_i = \frac{1}{1 - R_i^2} \qquad (2)$$

where R_i^2 is the coefficient of determination for the regression of variable X_i on all other independent variables in the model. The interpretation of the VIF coefficient is generally as follows:

– VIF = 1: No multicollinearity.

– 1 < VIF < 5: Moderate multicollinearity, which usually does not cause serious issues.

– VIF > 5: High multicollinearity, which can affect the reliability of parameter estimates.

– VIF > 10: Very high multicollinearity, requiring correction.

The VIF test serves as a crucial diagnostic tool for ensuring that the regression model provides valid and interpretable results. High multicollinearity may prompt adjustments, such as removing or combining variables to improve model stability.

Most academic studies agree that the maximum acceptable VIF threshold is 10 [13]. Upon calculating the VIF for the selected factors in the regression model, the following results were obtained: probability = 6.24, surprise = 1.21, Bullish = 9.19, Bearish = 7.47, and Slope = 9.56. As we can see from these results, for most factors, the VIF exceeds the value of 5, and for some, it approaches or exceeds 9, indicating a potential risk of multicollinearity. However, the context of the study suggests that these variables are of an economic nature. Some academic works argue that collinearity does not introduce bias nor cause instability in results for models with economic factors [14]. Another study indicates that in certain fields, such as international business research, multicollinearity is acknowledged, and researchers are advised to consider the context and data generation processes when making decisions about interpreting the results [15].

In the context of our study, we recognize that while the returns on assets may be influenced by a variety of factors, a specific set of variables that can partially explain the dynamics of returns can provide a basis for interpreting these factors and for further developing a model for optimal asset allocation.

Regarding the dependent variable data (asset returns), no additional data manipulations are required. It is important to note that the return calculated reflects the return for the previous period as of the day of observation. Accordingly, to assess the impact of factors on returns over a specific period, it is necessary to shift the data array backward by the corresponding period. For instance, in the case of annual returns, before performing regression analysis, the data must be shifted one year backward, so that each observation point reflects the actual return after one year. By aligning the factors with future returns, the model can more accurately capture the causal relationships and the predictive power of the chosen factors over time. Thus, this time-lagging procedure is crucial for identifying how factors, such as market expectations or investor sentiment, affect future asset performance.

Using the Spyder IDE and Python programming language, we conducted a multifactor linear regression analysis for each asset's return individually, across five different periods. As noted earlier, the return data was shifted back by the corresponding period. Below, Table 3 provides a summary of these results.

The primary focus when analyzing the results is the value of the coefficient of determination, R^2. As we can observe, with the increase in the investment period, the average value of R^2 increases from 0.10 for 3-month returns to 0.35 for 5-year returns. As being noted in study [16], in social research, values starting from 0.10 can be considered acceptable, provided that most independent variables are statistically significant. From Table 3, it can be observed that the number of non-significant variables is highest for the 3-month yield and lowest for the 1-year and 2-year periods. This can be explained by the likelihood that short-term asset behavior is less influenced by the selected factors and is more unpredictable.

As the investment period lengthens, the variables tend to have a more systematic influence on asset yields. However, even though the average R^2 value is highest for the 5-year period and the majority of assets show R^2 values greater than 0.1, the number of non-significant variables is higher compared to the 2-year and 1-year periods. This is most likely because the forecasting period is too long to accurately assess the impact of today's factor values on future yields, resulting in the non-significance of certain variables.

That said, this conclusion may vary depending on the specific asset. For example, as we can see from Table 4, the coefficient of determination for the 1-year return on the iShares MSCI Emerging Markets ex China ETF (EMXC) is 0,77, with all variables statistically significant at $p < 0{,}01$. Given the large number of observations (1433), it is difficult to challenge the conclusion that the selected set of factors significantly influences the yearly returns of the EMXC. On the other hand, there are up to 9 asset classes, that demonstrate significance below 0,10. Most probably these assets require more sophisticated methods to reveal hidden dependencies on the selected factors.

Conclusions from the study. The analysis highlights that theoretical factors impact asset classes differently. Bonds and commodities exhibit higher predictability, while equities show lower coefficients of determination due to their sensitivity to human behavior and a broader

Table 3

Summarized results of the regression analysis among all asset classes

Returns period:	**3-month**	**6-month**	**1-year**	**2-year**	**5-year**
Average R squared	0,10	0,14	0,17	0,23	0,35
Instances of insignificance of variables (p value > 0.05)					
P-value, Intercept	5	4	4	1	4
P-value, probability	14	5	5	5	6
P-value, surprise	2	1	0	1	3
P-value, Bullish	6	6	0	4	3
P-value, Bearish	2	2	3	3	5
P-value, Slope	8	3	4	2	0
Total	37	21	16	16	21
R^2 < 0,1	22	13	10	5	2
R^2 from 0,1 to 0,4	13	21	23	27	18
R^2 from 0,4 to 0,7	0	1	2	3	13
R^2 > 0,7	0	0	0	0	2

Source: calculated by authors

Table 4

Results of regression analysis of factors on 1-year returns

Asset	R-Square	Obser-vations	P-value, Intercept	P-value, probability	P-value, surprise	P-value, Bullish	P-value, Bearish	P-value, Slope
EMXC	0,61	1433	0,000	0,000	0,000	0,000	0,000	0,007
CEMB	0,40	2770	0,000	0,000	0,000	0,000	0,000	0,000
URA	0,36	3122	0,000	0,434	0,000	0,000	0,000	0,000
EMB	0,30	3859	0,000	0,000	0,000	0,012	0,000	0,000
BSV	0,28	4034	0,000	0,000	0,000	0,000	0,000	0,879
TIP	0,26	4877	0,000	0,000	0,000	0,000	0,000	0,000
BND	0,25	4036	0,000	0,000	0,000	0,000	0,000	0,000
VCIT	0,24	3373	0,000	0,000	0,000	0,012	0,000	0,000
XLY	0,23	6111	0,000	0,000	0,000	0,000	0,000	0,000
IYR	0,19	5736	0,000	0,043	0,000	0,000	0,006	0,000
gold	0,19	9195	0,000	0,000	0,000	0,000	0,000	0,000
IUSG	0,18	5709	0,009	0,000	0,000	0,000	0,000	0,000
VEA	0,18	3951	0,594	0,001	0,000	0,000	0,000	0,210
XLK	0,17	6111	0,000	0,000	0,000	0,000	0,176	0,000
XLV	0,16	6111	0,000	0,000	0,000	0,000	0,025	0,000
GBTC	0,15	1990	0,000	0,000	0,000	0,000	0,000	0,000
DBA	0,15	4091	0,000	0,000	0,000	0,000	0,000	0,000
XLI	0,15	6111	0,051	0,000	0,000	0,049	0,000	0,000
XLB	0,15	6111	0,000	0,000	0,000	0,000	0,000	0,000
IEF	0,13	5218	0,000	0,000	0,000	0,000	0,000	0,000
DBO	0,12	4091	0,000	0,190	0,000	0,000	0,000	0,000
^SP500-50	0,12	7532	0,000	0,000	0,000	0,000	0,000	0,921
SPY	0,11	9030	0,000	0,000	0,000	0,000	0,000	0,000
TLT	0,11	5218	0,000	0,000	0,000	0,003	0,000	0,000
WILL5000PR	0,11	9319	0,000	0,000	0,000	0,000	0,001	0,000
XLF	0,10	6111	0,000	0,000	0,000	0,000	0,058	0,007
silver	0,09	8540	0,000	0,000	0,000	0,000	0,000	0,000
XLP	0,09	6111	0,243	0,010	0,000	0,003	0,000	0,001
IUSV	0,08	5703	0,344	0,000	0,000	0,000	0,005	0,000
platinum	0,08	8147	0,000	0,874	0,000	0,000	0,000	0,000
EWJ	0,08	6809	0,017	0,000	0,000	0,000	0,357	0,000
PCOPPUSDM	0,06	8373	0,000	0,001	0,000	0,000	0,000	0,527
XLE	0,05	6111	0,000	0,031	0,000	0,000	0,000	0,007
EZU	0,05	5707	0,000	0,842	0,000	0,004	0,000	0,046
XLU	0,04	6111	0,000	0,991	0,000	0,007	0,000	0,001
Average R^2	**0,17**	**Instances of insigni-ficance (>0.05)**	4	5	0	0	3	4
Percentage of instances of insignificance			11%	14%	0%	0%	9%	11%

Source: calculated by authors

range of influencing factors. This suggests that investors should adjust their reliance on these factors depending on the asset class, interpreting them differently based on their specific influence.

Another key finding is that asset predictability improves with longer investment horizons, supporting the rationale for long-term investing, particularly beyond one year. Longer periods reduce the risk of impulsive decisions caused by short-term volatility and enable more structured portfolio planning. More stable patterns over time help investors make informed allocation decisions.

For investment periods exceeding a year, expectations about economic growth, inflation, risk premiums, and the future value of money play a crucial role in asset price dynamics. While the coefficients of determination are not always high enough for precise forecasting, the insights remain valuable for interpreting factor signals. These findings help investors refine asset allocation strategies, especially during market uncertainty, by integrating economic expectations into decision-making.

Future research could explore additional equity price factors, such as sentiment indices and volatility measures, or adopt machine learning for better modeling. Investigating time-varying relationships using dynamic models may offer insights into economic cycle effects. Expanding to global markets could also enhance understanding of regional factor dynamics. Finally, improving long-term return prediction models remains a valuable area for further study. While this research supports the usefulness of certain factors for extended forecasting, enhancing models with forward-looking data, real-time economic indicators, and refined expectations measures could lead to more accurate predictions. Such advancements would provide investors with stronger tools for long-term portfolio management and strategic asset allocation.

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